

Final report: Influence of human policies on lesser prairie-chicken (*Tympanuchus pallidicinctus*) ecology in a fragmented landscape

Prepared by: Evan P. Tanner^a, Samuel D. Fuhlendorf^a, R. Dwayne Elmore^a, Craig A. Davis^a

^aDepartment of Natural Resource Ecology and Management, Oklahoma State University,
Stillwater, OK 7407

TABLE OF CONTENTS

List of Tables.....	iii
List of Figures.....	v
Executive Summary.....	1
Background.....	2
Objective 1.....	3
Methods.....	3
Location Data.....	3
Environmental Data.....	4
Data Analysis.....	6
Roadside Bias Assessment.....	8
Results.....	9
Roadside Bias.....	24
Objective 2.....	28
Methods.....	28
Study site.....	28
Occurrence location data.....	28
Lesser prairie-chicken locations.....	28
Northern bobwhite and scaled quail locations.....	29
Additional data and spatial rarefication of location data.....	29
Environmental data.....	29
Data analysis.....	32
Post-hoc analysis.....	32
Results.....	33
Post-hoc results.....	38
Objective 3.....	48
Methods.....	48

Study site.....	48
Lesser prairie-chicken capture and monitoring.....	48
Lesser prairie-chicken movement.....	48
Vegetation monitoring.....	48
Data analysis.....	49
Movement analysis.....	49
Vegetation analysis.....	50
Results.....	50
Movement results.....	50
Vegetation response.....	59
Objective 4.....	61
Methods.....	61
Environmental data.....	63
Landcover data.....	63
Anthropogenic data.....	63
Other variables.....	63
Data analysis.....	64
Roost site habitat selection.....	64
Movement to roost analysis.....	64
Results.....	65
Discrete choice analysis.....	65
Movement to roost analysis.....	65
Discussion and summary.....	75
Conservation recommendations and future research opportunities.....	78
Literature cited.....	79

LIST OF TABLES

Table 1.1. Average estimates of model performance ^a for three different Maxent models of environmental suitability for lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) created using observations from eBird data, recorded in aerial surveys, and a model combining both datasets from March 15-May 15, 2012-2014.....	10
Table 1.2. Akaike's Information Criterion (AIC) model selection results for Maxent model performance of three lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) occurrence datasets based on different regularization multiplier values.....	15
Table 1.3. Average estimates of variable contribution ^a to model accuracy gain for three Maxent model sets of lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) environmental suitability created using observations from eBird data, recorded in aerial surveys, and a model combining both datasets from March 15-May 15, 2012-2014.....	22
Table 1.4. Mean beta coefficients and standard deviations (SD) for the two categorical environmental variables for Maxent models using three different lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) datasets: eBird, aerial survey, and a combination of the two (joint).....	23
Table 2.1. Average annual changes in the percent cover of plant functional groups and annual precipitation in Beaver County, Oklahoma from 2013-2015 as determined by the Rangeland Analysis Platform.....	31
Table 2.2. Average estimates of model performance for 30 replicates of Maxent models of the lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>), northern bobwhite (<i>Colinus virginianus</i>), and scaled quail (<i>Callipepla squamata</i>) in Beaver County, Oklahoma from April 1, 2013-July 1, 2015.....	35
Table 2.3. Average estimates of variable contribution to model accuracy gain for 30 replicates of Maxent models of the lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>), northern bobwhite (<i>Colinus virginianus</i>), and scaled quail (<i>Callipepla squamata</i>) in Beaver County, Oklahoma from April 1, 2013-July 1, 2015.....	36
Table 3.1. Akaike's Information Criterion adjusted for small sample size (AIC _c) model selection results for binomial generalized linear mixed effects models assessing the influence of the Conservation Reserve Program (CRP) on the probability of a lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) movement within Beaver County, OK from April 1, 2014-January 31, 2015.....	52
Table 3.2. Akaike's Information Criterion adjusted for small sample size (AIC _c) model selection results for Gamma distributed generalized linear mixed effects models assessing the influence of the Conservation Reserve Program (CRP) on lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) mean hourly step lengths (m) within Beaver County, OK from April 1, 2014-January 31, 2015.....	53

Table 3.3. Average values of vegetation metrics measured on a Conservation Reserve Program (CRP) pasture across 30 plots that experienced mid-contract managed grazing in Beaver County, OK.....	60
Table 4.1. Akaike's Information Criterion adjusted for small sample size (AIC_c) model selection results for discrete choice models assessing the influence of interactions between season and vegetation/anthropogenic variables on the roost site selection lesser prairie-chickens (<i>Tympanuchus pallidicinctus</i>) within Beaver County, OK from April 2014-May 2016.....	67
Table 4.2. Akaike's Information Criterion adjusted for small sample size (AIC_c) model selection results for discrete choice models assessing the influence of a vegetation global model (only containing vegetation-related variables) and an anthropogenic global model (only containing anthropogenic-related variables) on the roost site selection lesser prairie-chickens (<i>Tympanuchus pallidicinctus</i>) within Beaver County, OK from April 2014-May 2016.....	68
Table 4.3. Parameter estimates, 95% confidence intervals, and associated significance values for variables within the vegetation global model as calculated from a discrete choice model assessing the influence of a vegetation global model on the roost site selection lesser prairie-chickens (<i>Tympanuchus pallidicinctus</i>) within Beaver County, OK from April 2014-May 2016.....	69
Table 4.4. Akaike's Information Criterion adjusted for small sample size (AIC_c) model selection results for Gamma distributed GLMMs assessing the influence of CRP on the movement lengths of movements to roost sites for lesser prairie-chickens (<i>Tympanuchus pallidicinctus</i>) within Beaver County, OK from April 2014-May 2016.....	70

LIST OF FIGURE

Figure 1.1. Lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) site suitability estimated through Maxent using lesser prairie-chicken occurrence data from aerial surveys (A), eBird observations (B), and an equal combination of locations from both data sources (i.e., a joint model [C]) from March 15-May 15, 2012-2014.....	12
Figure 1.2. The null distribution of the species distribution model overlap statistic <i>I</i> created from 100 replicates of Maxent models that compared randomly selected lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) locations from the aerial survey dataset to locations from the eBird dataset.....	13
Figure 1.3. Estimates of centroid shifts between Maxent models for the lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) as determined by three occurrence datasets; aerial survey, eBird, and joint (combined aerial survey and eBird).....	14
Figure 1.4. Relationship between environmental ^a variables and probability of suitability (and associated standard deviation bars) for the lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) as estimated through Maxent using occurrence data from aerial surveys from March 15-May 15, 2012-2014.....	17
Figure 1.5. Relationship between environmental variables and probability of suitability (and associated standard deviation bars) for the lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) as estimated through Maxent using occurrence data from the eBird dataset from March 15-May 15, 2012-2014.....	19
Figure 1.6. Relationship between environmental variables and probability of suitability (and associated standard deviation bars) for the lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) as estimated through Maxent using occurrence data from combined aerial survey/eBird data from March 15-May 15, 2012-2014.....	20
Figure 1.7. Difference in road density by existing vegetation cover (EVC) ^b type through the lesser prairie-chicken's (<i>Tympanuchus pallidicinctus</i>) distribution as determined by a Kruskal-Wallis test.....	26
Figure 1.8 Difference in road density ^a by existing vegetation height (EVH) categories through the lesser prairie-chicken's (<i>Tympanuchus pallidicinctus</i>) distribution as determined by a Kruskal-Wallis test.....	27
Figure 2.1. Probability of environmental suitability for the lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) in relation to whether or not the land cover type was actively enrolled in the Conservation Reserve Program (CRP).....	37
Figure 2.2. Binary suitability output maps for the lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) and northern bobwhite (<i>Colinus virginianus</i>) as predicted by 30 replicated Maxent models in Beaver County, Oklahoma from April 1, 2013-July 1, 2015.....	40

Figure 2.3. Binary suitability output maps for the lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) and scaled quail (<i>Callipepla squamata</i>) as predicted by 30 replicated Maxent models in Beaver County, Oklahoma from April 1, 2013-July 1, 2015.....	41
Figure 2.4. Binary suitability output maps for the northern bobwhite (<i>Colinus virginianus</i>) and scaled quail (<i>Callipepla squamata</i>) as predicted by 30 replicated Maxent models in Beaver County, Oklahoma from April 1, 2013-July 1, 2015.....	42
Figure 2.5. Moran's <i>I</i> statistic for measuring niche similarity between lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>), northern bobwhite (<i>Colinus virginianus</i>), and scaled quail species distribution models as predicted by 30 replicated Maxent models in Beaver County, Oklahoma from April 1, 2013-July 1, 2015.....	43
Figure 2.6. Range overlap statistics across varying logistic threshold values for lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>), northern bobwhite (<i>Colinus virginianus</i>), and scaled quail species distribution models as predicted by 30 replicated Maxent models in Beaver County, Oklahoma from April 1, 2013-July 1, 2015.....	44
Figure 2.7. Non-metric multidimensional scaling of environmental data ^a associated with discrete maps derived from logistic outputs of Maxent models created from northern bobwhite (<i>Colinus virginianus</i>) and lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) data in Beaver County, OK from 2013-2015.....	45
Figure 2.8. Non-metric multidimensional scaling of environmental data ^a associated with discrete maps derived from logistic outputs of Maxent models created from scaled quail (<i>Callipepla squamata</i>) and lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) data in Beaver County, OK from 2013-2015.....	46
Figure 2.9. Non-metric multidimensional scaling of environmental data ^a associated with discrete maps derived from logistic outputs of Maxent models created from scaled quail (<i>Callipepla squamata</i>) and northern bobwhite (<i>Colinus virginianus</i>) data in Beaver County, OK from 2013-2015.....	47
Figure 3.1. Mean hourly step lengths of lesser prairie-chickens (<i>Tympanuchus pallidicinctus</i>) in Beaver County, OK from April 1, 2014-January 31, 2015.....	54
Figure 3.2. Probability of a lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) moving across subsequent hourly locations in relation to whether or not a subsequent location was within the Conservation Reserve Program (CRP) in Beaver County, OK.....	55
Figure 3.3. Mean hourly step length (m) of lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) movements in relation to whether or not the movement ended within the Conservation Reserve Program (CRP) in Beaver County, OK.....	56
Figure 3.4. Mean hourly step length (m) of lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) movements in relation to the proportion of the step length located within the Conservation Reserve Program (CRP) in Beaver County, OK.....	57

Figure 3.5. Mean hourly step length (m) of lesser prairie-chicken (<i>Tympanuchus pallidicinctus</i>) movements in relation to the proportion of the step length located within the Conservation Reserve Program (CRP) in Beaver County, OK.....	58
Figure 4.1. Average hourly movement (m) distances of lesser prairie-chickens (<i>Tympanuchus pallidicinctus</i>) from April 2013-May 2016 in Beaver County, OK.....	62
Figure 4.2. Number of lesser prairie-chickens (<i>Tympanuchus pallidicinctus</i>) contributing to nocturnal roost site selection samples by season from April 2013-May 2016 in Beaver County, OK.....	71
Figure 4.3. Average movement of lesser prairie-chickens (<i>Tympanuchus pallidicinctus</i>) to and from roost sites as well as their average diurnal movements by season in Beaver County, OK from April 2013-May 2016.....	72
Figure 4.4. Relationship between the proportion of a lesser prairie chicken's (<i>Tympanuchus pallidicinctus</i>) movement to a roost site contained within CRP and the mean hourly step length of the movement to a roost site as determined from a GLMM.....	73
Figure 4.5. Relationship between whether or not a roost site of a lesser prairie chicken (<i>Tympanuchus pallidicinctus</i>) was located in CRP and the mean hourly step length of the movement to a roost site as determined from a GLMM.....	74

EXECUTIVE SUMMARY

Agricultural and development policies influence ecological patterns and processes across both space and time. In response to policy-driven changes to landscapes, policy makers initiated conservation programs such as the Conservation Reserve Program (CRP) to ameliorate the impacts of modern agricultural practices on private lands in the U.S. The CRP was established in 1985 to promote soil conservation through replacing highly erodible croplands with perennial and annual vegetation cover, but it also resulted in ecological benefits such as providing habitat for species of conservation concern. The lesser prairie-chicken (*Tympanuchus pallidicinctus*; hereafter “LPC”) is a declining species of North American prairie grouse that has benefited in recent decades from the enrollment of CRP in the Southern Great Plains. Despite the potential of CRP to influence lesser prairie-chicken conservation, empirical evidence of how individuals and populations function in relation to spatially explicit CRP cover is lacking. We sought to understand how LPCs responded to CRP cover across multiple spatial extents through the integrated use of different datasets associated with LPC occurrences and movement patterns. Specifically, we determined the responses of LPCs to CRP cover at three spatial extents: distribution level, county level, and pasture level. Within this hierarchical framework, our objectives were to 1) determine how CRP influences LPC habitat suitability through integration of disparate occurrence datasets throughout the LPC distribution, 2) determine the potential of areas of high conservation value for LPCs on secondary species of management value (i.e., upland gamebirds) during changing environmental conditions, 3) determine how mid-contract management (i.e., grazing) of CRP influences movement patterns of LPCs, and 4) determine how CRP influences nighttime roost site selection and movement patterns to roost sites. With regard to species distribution models across the LPC’s current range, all models (except one with a roadside bias) indicated a positive relationship between LPC presence and CRP across all examined scales, indicating this relationship was scale-invariant and that CRP was a primary driver of space use. Furthermore, at a county extent, CRP remained a primary factor influencing environmental suitability for LPCs when accounting for changing vegetation conditions associated with annual precipitation events. When CRP was present on the landscape, the probability of suitability for the LPC was 74.27% (SE = 0.001), 74.68% (SE = 0.002), and 75.05% (SE = 0.006) during 2013, 2014, and 2015, respectively. Conversely, areas not comprised of CRP cover had a probability of suitability for LPCs of 27.58% (SE = 0.04), 29.30% (SE = 0.04), and 23.73% (0.06) during 2013, 2014, and 2015, respectively. However, CRP was not an influential variable in predicting probability of suitability for other game species (the northern bobwhite [*Colinus virginianus*] and scaled quail [*Callipepla squamata*]), and niche similarities were low between quail and LPC distribution models. This suggests that the use of northern bobwhite and scaled quail management as an umbrella approach to help benefit LPC conservation is likely not warranted. Additionally, practices such as managed grazing associated with mid-contract CRP management did not significantly influence vegetation or LPC movement patterns associated with CRP patches experiencing mid-contract management. Finally, we provide the first evidence of CRP influencing nocturnal roost site selection and movement patterns to roost sites, filling a knowledge gap during this period in the LPC’s life-history. Specifically, vegetation was more important to roost site selection than the influence of anthropogenic features. Of the vegetation variables influencing roost site selection, LPC located roost sites closer to CRP, their lek of capture, croplands, and mixed grass prairie than would be expected at random. Of

these, CRP was the most influential variable influencing roost site selection. Moreover, our models indicated that as movements to the roost site contained more CRP along the step length, movements decreased whereas movements to the roost were greater when a roost site was in CRP as opposed to outside CRP. This suggests that individuals located outside of CRP before sunset are moving longer distances to get to roost sites in CRP, but if they were already located in CRP before moving to the roost site (i.e., 100% of their movement to the roost was in CRP), they moved significantly less to get to their roost within CRP. Our results, along with a growing body of literature, suggest that patches of CRP are playing a key ecological role in maintaining useable space throughout the LPC's distribution. Based on our results, a list of conservation recommendations and future directions are outlined to help provide guidance to the NRCS for LPC conservation.

BACKGROUND

Agricultural and development policies influence ecological patterns and processes across both space and time, and can play an important role in the conservation of organisms within landscapes that are impacted by fragmentation and anthropogenic disturbance (Meyer 1995, Donald and Evans 2006, Tanner and Fuhlendorf 2018). Within the Great Plains of North America, human-influenced land cover change over the past two centuries has transformed previously extensive open grasslands into a mosaic of irrigated croplands (Drummond et al. 2012), woodlands (Archer 1994, Engle et al. 1995), remnant grasslands, and industrial infrastructure associated with energy development. A culmination of these human-influenced land cover changes have resulted in North American grasslands being considered some of the most altered and threatened ecosystems (Samson and Knopf 1994), with associated populations of plants and wildlife experiencing distribution-wide declines due to these trends (Knopf 1994, Fuhlendorf and Engle 2001, Brennan and Kuvlesky 2005, Ratajczak et al. 2012).

To address concerns about the loss of grasslands and their historical ecological patterns and processes, policy makers initiated conservation programs to ameliorate the impacts of modern agricultural practices on private lands. The Conservation Reserve Program (CRP) is one such program that was established in 1985 to help promote soil conservation through replacing highly erodible croplands with perennial and annual vegetation cover. With approximately 9.06 million ha enrolled within the United States as of February 2019, the CRP has significantly altered land cover patterns throughout the Great Plains (Tanner and Fuhlendorf 2018) and has resulted in providing ecological benefits to a host of species of conservation concern (Delisle and Savidge 1997, Hagen et al. 2016, Sullins et al. 2019).

One species that has benefited from the CRP is the lesser prairie-chicken (*Tympanuchus pallidicinctus*; hereafter "LPC"), a North American prairie grouse that has experienced population declines and a reduction in its distribution for decades (Silvy 2006). Land enrolled in the CRP has been identified as critical to LPC habitat throughout portions of its distribution due to the influence of habitat heterogeneity and grassland connectivity (Jarnevich and Laubhan 2011; Spencer et al. 2017; Sullins et al. 2018). Despite the potential of CRP to influence lesser prairie-chicken conservation, empirical evidence of how

individuals and populations function in relation to spatially explicit CRP cover is widely lacking. This is particularly true for understudied periods of the LPC's life-history (i.e., roosting locations). Furthermore, the spatial scale at which we assess LPC responses to CRP enrollment may influence our understanding of these relationships if scale mismatch occurs in which relationships vary across spatial and temporal scales. Both the spatial organization and management practices (i.e., mid-contract management such as prescribed grazing, shallow disking and interseeding, etc.) associated with CRP can be highly dynamic and thus a multi-scale assessment of how LPCs respond to CRP on the landscape could help further corroborate the benefits of CRP enrollment to LPC populations.

Finally, coupled with spatial variability in CRP enrollment and practices, is the temporal variability associated with vegetation within CRP cover due to changing environmental conditions. Precipitation and temperature conditions have direct impacts on vegetation dynamics such as influencing species richness and the total cover of grass and forbs within ecosystems (Collins et al. 1987). Such dynamics in habitat quality could influence how or when LPCs use CRP areas, in which these areas may be more vital to LPC population stability during periods of extreme drought (Ross et al. 2016). Thus, a temporally variable assessment of CRP benefits to LPCs may help highlight how these relationships change with variable rangeland conditions.

In this study, we sought to understand how LPCs responded to CRP cover across multiple spatial extents through the integrated use of different datasets associated with LPC occurrences and movement patterns. Specifically, we determined the responses of LPCs to CRP cover at three spatial extents: distribution level, county level, and pasture level. Within this hierarchical framework, our objectives were to 1) determine how CRP influences LPC habitat suitability through integration of disparate occurrence datasets throughout the LPC distribution, 2) determine the potential of areas of high conservation value for LPCs on secondary species of management value (i.e., upland gamebirds) during changing environmental conditions, 3) determine how mid-contract management (i.e., grazing) of CRP influences movement patterns of LPCs, and 4) determine how CRP influences nighttime roost site selection and movement patterns to roost sites. For simplicity, we have separated the Methods and Results sections by each objective rather than attempting to coalesce all information into a single Methods and Results section.

OBJECTIVE 1 – Determine how CRP influences LPC habitat suitability through integration of disparate occurrence datasets throughout the LPC distribution

METHODS

Location Data

Our aerial survey LPC lek location data were compiled by the Western Association of Fish and Wildlife Agencies (WAFWA) from 2012 – 2014 (McDonald et al. 2014). These data were collected by West Ecosystems Technology, Incorporated (Cheyenne, Wyoming, USA) using transect, helicopter-based surveys to locate leks across the LPC's distribution. Two observers sat in the rear left and right seats and a third observer in the front left seat of the

helicopter during surveys. Transects were flown 25 m above ground at 60 km per hour from sunrise until approximately 2.5 hours after sunrise from March 15 to May 15 during each year. In total, 283, 15 x 15 km cells were sampled. Observations of five birds or less were ground-truthed to confirm the actual presence of a lek. Observations with more than five birds were considered lek sites.

We acquired LPC observations from 2012 through 2014 compiled by eBird, a freely-available website that gathers, organizes, maintains, and disseminates information about bird observations from the public (Sullivan et al. 2009). Data submission requires the observer to report the date, time, location, distance traveled, effort (time), species observed, and number of individuals observed and any relevant comments or images. Observations of species that are rare for the location, time of year, or number observed are flagged for review by a regional editor (Sullivan et al. 2009). Because multiple observers can report LPCs at the exact same location, we filtered our data to include only observations that were spatially independent. We also omitted observations where the observer reported “moving” the location in the interest of the privacy of the landowner, or that were flagged for review but not verified by a regional editor. Finally, we only included eBird locations with detailed geographic coordinates while omitting those reported at larger scales (i.e., ¼ county scale) due to landowner sensitivity.

We used the spatial rarefaction tool in SDMtoolbox (Brown 2014) to reduce spatial autocorrelation of our location data in ArcGIS 10.2 (ESRI, Redlands, CA). LPCs have been shown to have high site fidelity associated with the leks they were captured at, with a majority (up to 98%) of locations of radio-marked birds being within 5 km of the lek where they were captured (Kukal 2010). Therefore, we spatially rarefied our location data by 5 km. Since eBird data are associated with a semistructured citizen science project (Kelling et al. 2019), we further standardized information associated with this database by only including eBird observations where the distance traveled by the eBird user was ≤ 5 km or effort area was $\leq 25\text{km}^2$ to match the grain of our environmental data (see below).

Once both occurrence datasets were spatially rarefied, we randomly removed locations from the dataset with more samples so that both rarefied datasets had the same amount of occurrence locations. Finally, we created a joint occurrence dataset that incorporated occurrence locations from both the aerial survey data and the eBird data to simulate collating disparate datasets to maximize coverage of species' occurrences within the species' distribution; this is a common practice if low sample sizes are a concern when running SDMs. To make sure each dataset was equally represented in the joint occurrence dataset, we randomly selected an equal amount of locations from the eBird and aerial survey datasets until it had an equal sample size as the final rarefied datasets.

Environmental Data

LPC occupation of an area is often determined by the vegetation types present, amount of the landscape covered by those vegetation types (Jarnevich and Laubhan 2011; Timmer et al. 2014; Hagen et al. 2016), and associated vegetation heights. We used the 2013 existing

vegetation cover (EVC) and existing vegetation height (EVH) layers (LANDFIRE 2013) as environmental layers in our analysis. These layers were created using a combination of field-based data and geospatial data layers under the direction of the Wildland Fire Leadership Council. Both layers had a cell size of 30 m, but were scaled up to a cell size of 5 km using Block Statistics and the Resample tools with a majority rule in ArcGIS 10.2 (ESRI, 2011). Thus, EVC and EVH categories represented in each 5 km pixel ultimately defined what the matrix of each 25 km² area was composed of. The EVC layer represented percent cover of the live canopy layer of the dominant vegetation type from 0 to 100% and was divided into three major classes: tree, shrub, and herbaceous. The layer was presented as categorical data where each cover class is separated into 10% cover categories (i.e., herbaceous cover ≥ 20 and $< 30\%$). Cropland and developed vegetation types (areas with anthropogenic structures and infrastructure) were also included in the EVC layer. The EVH represented the average height of the dominant vegetation and included four classes: tree, shrub, herbaceous, and forest. Heights were recorded by class in at least 0.5 m intervals and up to 10 m intervals for the forest class. A more detailed description of each category within these two variables can be found at <https://www.landfire.gov/documents/LF-GAPMapUnitDescriptions.pdf> (accessed 9/4/2019).

Anthropogenic development negatively influences survival and causes displacement of grouse (Pitman et al. 2005; Wolfe et al. 2007; Hagen 2010; Hovick et al. 2014). Therefore, we incorporated anthropogenic impacts into our environmental layer dataset. To measure anthropogenic impacts, we used the global human footprint dataset available through the Socioeconomic Data and Applications Center and compiled by the Wildlife Conservation Society and Center for International Earth Science Information Network (Columbia University 2005). This layer incorporates human population pressure, land use, infrastructure, and access into one continuous data set ranging from 0 – 100 where 0 is no impact and 100 is maximum impact. The cell size is 1 km, however we resampled the layer by averaging to 5 km.

The global human footprint dataset does not specifically incorporate oil and gas wells, which can impact LPC site occupation (Hunt and Best 2010) and have been important to predicting LPC lek density (Timmer et al. 2014). The Critical Habitat Assessment Tool (CHAT) provides a measure of oil and gas well density within a 1 square mile grid that is available for download through the Kansas Biological Survey (kars.ku.edu/maps/sgpchat). We downloaded the oil and gas well density layer from the CHAT and resampled the layer to a 5 km resolution.

The amount of land enrolled in the Conservation Reserve Program (CRP) is also important in predicting LPC occupation (Jarnevich and Laubhan 2011; Hagen et al. 2016). CRP provides annual rental payments for a period of 10-15 years to landowners enrolled in exchange for “retiring” and establishing grass cover on former cropland (Stubbs 2014). CRP is influential in structuring multi-scale connectivity of grasslands (Tanner and Fuhlendorf 2018) and has been determined critical to past and current LPC conservation efforts (Spencer et al. 2017; Sullins et al. 2018). The CHAT contains a CRP layer detailing the number of acres enrolled

in the program in a 1 square mile grid. We resampled this layer by sum to represent the percentage of CRP within a 5 km resolution cell.

The environmental layers were clipped to the extent of the counties within the LPC distribution as defined by the CHAT. We used the CHAT to help define our study extent as it is the spatial representation of the LPC Range Wide Plan (RWP) and functions as a common resource for scientists, managers, industry, and the public to help identify priority habitat (Southern Great Plains Crucial Habitat Assessment Tool, 2013. kars.ku.edu/maps/sgpchat/). Furthermore, we chose this extent as it represented the spatial coverage of environmental layers used and provided the CHAT tool. Counties were selected for the CHAT if they intersected a 10 km buffer that was placed around known LPC leks throughout the species' distribution. The LPC distribution included 105 counties located in New Mexico, Texas, Oklahoma, Kansas, and Colorado. We were most interested in examining the impact of using location data from different sources on our modeling efforts; therefore, we limited our environmental layers to those most likely to impact LPC potential distribution based on our knowledge of prairie grouse and existing literature.

Data Analysis

We used maximum entropy modeling to generate LPC probability of distribution models with Maxent modeling software version 3.3.3k (Phillips et al. 2006; Elith et al. 2010). Maxent has proven capable of accurately modeling the probability of environmental suitability for a variety of species over a range of environmental conditions (Phillips and Dudik 2008), including grouse (Hovick et al. 2015; Jackson et al. 2015). Maxent compares environmental conditions at known LPC locations to all available conditions within the study extent (the counties within the LPC distribution), and then estimates the probability of suitability for the focal species.

To assess the potential of citizen science data for use in LPC distribution modeling, we created three different model sets representing three types of occurrence data: an aerial survey model, an eBird model, and a joint model where the aerial survey and eBird location data were combined. Before creating models, we eliminated highly correlated environmental variables ($|r| > 0.7$ [Dormann et al. 2013]) from our five environmental layers: EVC, EVH, global human footprint, number of wells (from CHAT), and % of CRP within a 5 km resolution cell (from CHAT). For initial models we withheld 30% of the location data in each model set for accuracy testing. Each model set was replicated 100 times using a bootstrapping method in Maxent. The average percent contribution from these 100 replicates was reported for all variables and used to assess variable importance. Variables that were found to have negligible contribution (<5%) were omitted (Sahlean et al. 2014).

As metrics of model performance, we reported the area under the curve (AUC) of the receiver operating characteristic (ROC) and the standardized test omission error. The AUC measures the discriminatory capacity of the model such that a value of 0.5 is no better than random and a value of 1.0 would indicate a perfect prediction of site suitability by the model. Models with an AUC value >0.75 are generally considered informative (Swets 1988;

Fielding and Bell 1997; Elith 2002), though evaluating models with AUC alone may be misleading or violate AUC theory when modeling efforts using background data in place of true absence data, as our models do (Jiménez-Valverde 2012). Previous work evaluating the performance of species distribution models have used the True Skill Statistic (TSS) as an alternative to the AUC metric as it accounts for both omission and commission errors while also correcting for an inherent dependence on species prevalence, which could bias certain performance metrics (Allouche et al. 2006). However, recent research has illustrated that the TSS can be misleading within a presence-pseudoabsence framework and thus reliability metrics should be used when prevalence is unknown (Leroy et al. 2018). Thus, we used the Continuous Boyce Index (CBI) as a reliability metric to assess model performance in our study (Boyce et al. 2002; Hirzel et al. 2006). The CBI measures how model predictions differ from random distributions of observed presence data across the gradient of model prediction values. This metric ranges from -1 to +1 in which positive values indicate models where predictions agree with the actual distribution of the presence data, a value of 0 indicates a model that is no different from a random model, and negative values indicate a model that predicts the opposite distribution of the presence data. Finally, we used the standardized test omission error (Wilson et al. 2013) to further assess model performance. This metric is calculated by estimating the test omission rate (false negatives) for each model replicate ($n = 100$ per data set) based on a binary suitability map which is standardized to have the same percent area of suitability. Here we used 10% training presence as the threshold to reclassify the Maxent continuous suitability values to binary (presence above the threshold and absence at or below the threshold). We chose this threshold rule as it is useful when reliability and precision of occurrences is likely variable (i.e., eBird data; Rebelo and Jones 2010) where probability of presence was greater than 10%. The percent area of suitability was set as the mean percentage of suitable area estimated across all model runs for each occurrence dataset. Incorporating this metric allowed for a standardized approach to compare congruence of models across different input datasets.

Our objective was to compare the effect of location data between the three model sets; therefore, we standardized the influence of our environmental data at background (i.e., pseudo-absence) points across the three model sets. To address this, we created a background bias file (i.e., background points) by randomly selecting 50% of the pixels within our study extent (10,219 pixels). Using this bias file ensured that the background cells used for all three model sets were identical. We then specified that 10,219 background points were to be used by Maxent, which is $> 10,000$ and therefore sufficient to represent the environment available (Phillips and Dudik 2008).

To account for potential issues of model complexity (i.e., overfitting), we built Maxent models for each occurrence dataset with differing regularization multiplier values after removing highly correlated ($|r| > 0.70$) and poorly contributing ($< 5\%$ contribution) variables (Radosavljevic and Anderson 2014). The regularization multiplier is a coefficient specified by the user that is applied to the beta parameter of each feature class (i.e., a set of transformations of the original covariates [Elith et al. 2011]) in a model and alters the overall level of regularization (i.e., a penalty for each term included in a model) for each feature

class (Anderson and Gonzalez 2011, Radosavljevis and Anderson 2014) We built models with regularization multiplier values of 0.25, 0.50, 1.00, 1.50, 2.00, 4.00, 6.00, 8.00, and 10.00 and then selected the best performing model through the Model Selection function of ENMTools (Version 1.4.4; Warren et al. 2010) that retains the model with the lowest Akaike Information Criterion (AIC) score. The best performing model based on AIC values was the final model used to map environmental suitability and compare performance metrics of models across aerial survey, eBird, and joint occurrence datasets.

We compared outputs of the three model sets to one another using the *I* statistic, a measure of niche similarity, in ENMTools. The *I* statistic directly compares model estimates of environmental suitability for each cell between models, thus making the *I* statistic a threshold-independent method of comparing model output (Warren et al. 2008; Warren et al. 2010). Values for this statistic range from 0 (no overlap) to 1 (complete overlap). A null distribution of the *I* statistic was created in the ENMTools identity test function from 100 Maxent runs. The null distribution was created by pooling the occurrence points (both survey and eBird together) and randomizing their identities to create two new random occurrence datasets and estimating the *I* statistic across the 100 pseudoreplicates (Warren et al. 2008). We then compared the empirical *I* statistic (which was estimated from the true occurrence datasets) to the null distribution and determined significant differences between the values if the empirical *I* statistic did not overlap the null distribution. Finally, we compared distribution changes between all three SDMs by using the Centroid Changes tool in the SDMtoolbox (Brown 2014), which calculates the shift in SDM centroids between two different models.

Roadside Bias Assessment

To understand the potential impact of spatial biases in our occurrence datasets associated with roads (i.e., roadside bias), we calculated a road bias metric used by Kadmon et al. (2004):

$$Road\ Bias_d = \frac{n_d - p_d N}{\sqrt{p_d(1 - p_d)N}}$$

where n_d is the number of occurrences within a distance (d) from a road, p_d is the probability for a location to be within the distance (d) of the nearest road, and N is the total number of occurrences in each data set (i.e., aerial survey and eBird data sets). The independent probability (p) for a location to be within d of the nearest road is estimated by creating random points equal to N for each data set within the study extent and then determining the fraction of random points located within d . This metric is estimated from the normal approximate to the binomial distribution (Kadmon et al. 2004) and is distributed like a standard normal variable. Thus, using a one-tailed test, the metric would indicate a significant bias near roads for values greater than 1.64 and a significant bias away from roads for values less than -1.64 ($\alpha = 0.05$). However, we used a two-tailed test as we wanted to determine a bias with no specific direction specified (i.e., testing both positive and negative biases together), thus values greater than 1.94 and less than -1.94 were considered significant

for a positive and negative roadside bias ($\alpha = 0.05$). As we were most interested in direct effects of roads, we set d to 250 meters (Kadmon et al. 2004) for both data sets.

Finally, to determine if any of our environmental variables were highly correlated with roads, we estimated a Pearson's r for all continuous variables and used a Kruskal-Wallis test and a Tukey's Multiple Comparison test for our two categorical variables. For continuous variables, a $|r| > 0.7$ was considered highly correlated. Because our spatial grain was set at 5 km, we calculated road density for our correlation and Kruskal-Wallis tests using the Line Density tool in ArcGIS 10.2 to estimate the density of roads within each 5 km pixel ($\text{km}/25 \text{ km}^2$) and related this variable to our environmental variables. For all road-related analyses, we used road GIS layers for Colorado (<https://data.colorado.gov/>), Kansas (<https://www.kansasgis.org/>), New Mexico (<http://rgis.unm.edu/>), Oklahoma (<http://gis-okdot.opendata.arcgis.com/>), and Texas (<http://gis-txdot.opendata.arcgis.com/>) which represented the five states within the LPC's distribution.

RESULTS

From March 15-May 15, 2012 to 2014, a total of 106 LPC leks were detected by aerial surveys. Of the 106 locations, 12 also contained greater prairie-chickens (*Tympanuchus cupido*) and were recorded as "mixed" leks. We included these leks in our analysis as they were representative of LPC site occupation. Spatial rarefaction of the aerial survey locations reduced our sample size from 106 to 68 leks. From January 2012 to December 2014, 522 observations of LPCs were reported to eBird at 140 spatially independent sites. Most (78.6%) LPC observations were reported in March and April, and approximately half (49.8%) of the observations were made by six observers. Although there were observations that occurred outside of the March-May period for the eBird dataset, we only included those locations occurring from March 15-May 15, 2012 to 2014 in our analyses to match the temporal extent of the aerial survey data. As the aerial survey occurrence dataset had the lowest sample size after spatial rarefaction, all final occurrence datasets used for modeling purposes had a sample size of 68 (Table 1.1).

Table 1.1. Average estimates of model performance^a for three different Maxent models of environmental suitability for lesser prairie-chicken (*Tympanuchus pallidicinctus*) created using observations from eBird data, recorded in aerial surveys, and a model combining both datasets from March 15-May 15, 2012-2014. AUC^b values > 0.75 indicate good model performance; lower omission error values are associated with higher model performance; the Continuous Boyce Index metric ranges from -1 to +1, with positive values indicating agreement with known presence data.

Location type	Occurrence locations (<i>n</i>)	Average test AUC ^b	Average standardized test omission (%)	Continuous Boyce Index
Aerial survey	68	0.76 (0.75-0.77)	23.4 (21.3-25.7)	0.73 (0.68-0.80)
eBird	68	0.76 (0.74-0.77)	23.8 (21.6-25.9)	0.79 (0.73-0.85)
Joint	68	0.70 (0.69-0.71)	24.9 (22.6-27.2)	0.76 (0.70-0.81)

^a 95% confidence intervals are indicated in parentheses.

^b Area under the curve of the receiver operating characteristic.

Based on AIC values, a regularization multiplier value of 1.5, 0.25, and 1 were used for the aerial survey, eBird, and joint models, respectively (Table 1.2). No other models were within a ΔAIC of <2 , therefore we only considered these three regularization multiplier values moving forward. Average binary estimates of the percent area estimated as suitable were 43.84%, 45.89%, and 50.08% for the aerial survey, eBird, and joint models, respectively. The average test AUC was ≥ 0.7 for all three models, with the greatest average test AUC reported for the aerial survey model (0.76; Table 1.1). Furthermore, the average ($\pm SE$) test omission was lowest in the aerial survey model ($18.58 \pm 0.97\%$; Table 1.1) and greatest in the joint model ($20.15 \pm 0.97\%$), though the difference between the average standardized test omission rates across all three model sets were not different based on overlapping confidence intervals. The highest CBI was estimated for the eBird model, though all three model sets had overlapping confidence intervals for CBI values. Based on these performance metrics, all three model sets had good performance. Logistic Maxent output maps (Figure 1.1) and probability distributions of site suitability between the three models were found to have a large degree of overlap (I statistic range = 0.930 to 0.978). The I statistic did not fall within the null distribution ($P < \text{observed} = 0.01$), indicating that the probability distributions of the eBird model and aerial survey model were significantly different (Figure 1.2). However, we did not consider this difference to be biologically significant as the empirical I statistic was 0.929 while the null distribution ranged from 0.94 to 0.99. Furthermore, when calculating SDM centroid shifts between our three model sets, we estimated a 67.56 km northeast shift from the survey to eBird model, a 42.25 km southwest shift from the eBird to joint model, and a 32.81 km northeast shift from the survey to joint model, indicating minimal shifts in the center geographic region for the LPC across model sets (Figure 1.3).

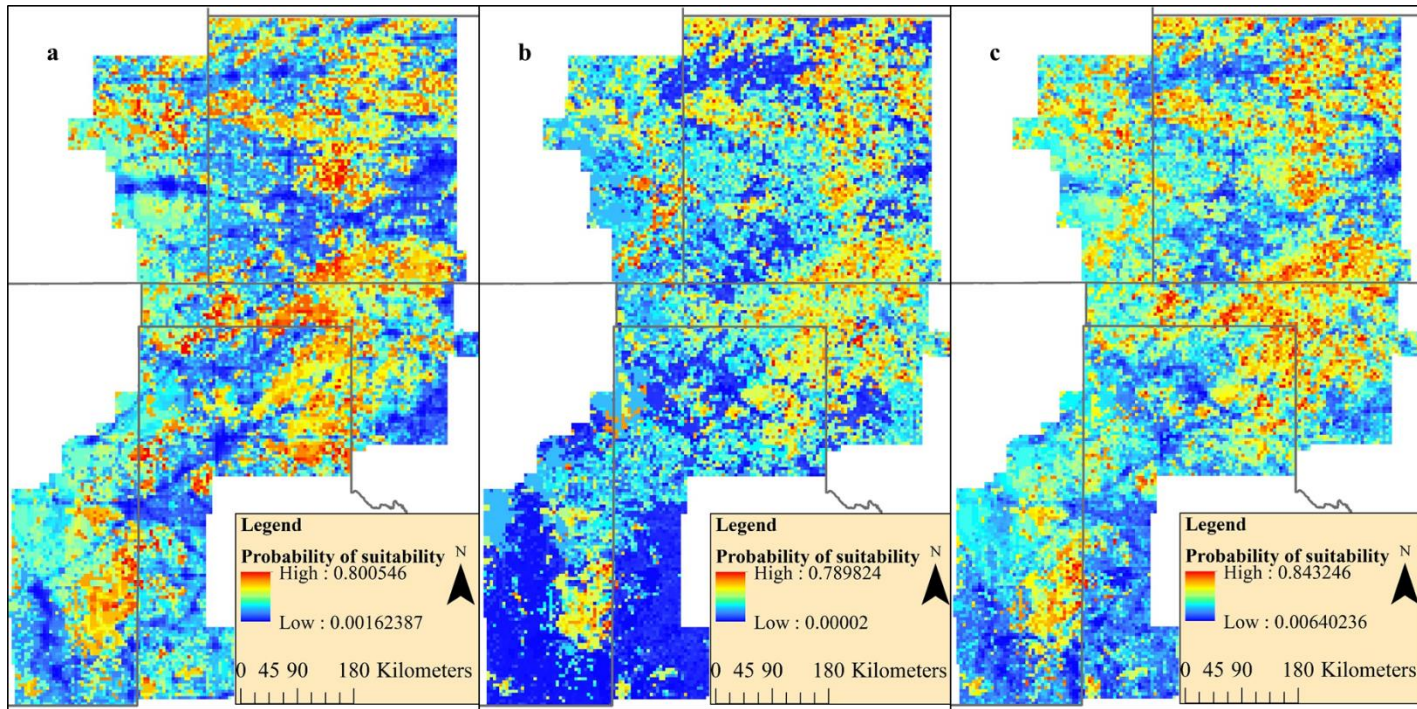


Figure 1.1. Lesser prairie-chicken (*Tympanuchus pallidicinctus*) site suitability estimated through Maxent using lesser prairie-chicken occurrence data from aerial surveys (A), eBird observations (B), and an equal combination of locations from both data sources (i.e., a joint model [C]) from March 15-May 15, 2012-2014. Overlaid black lines indicate state political boundaries.

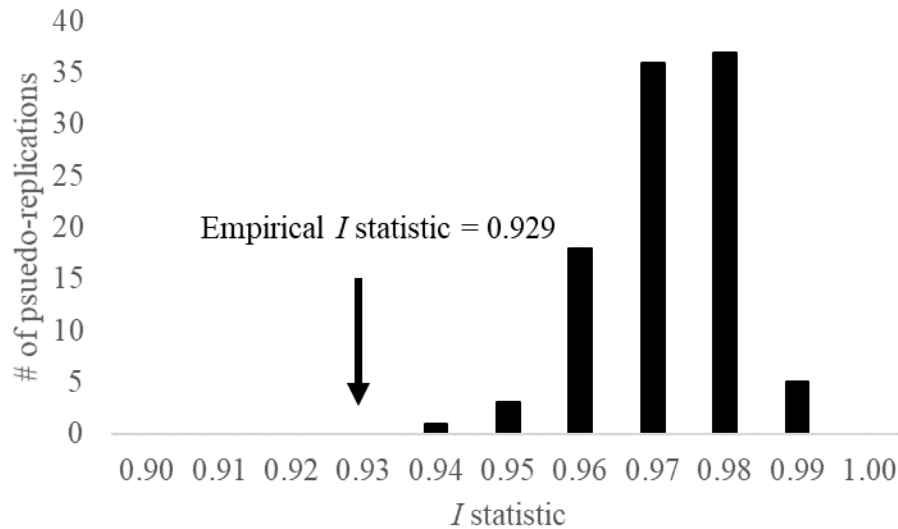


Figure 1.2. The null distribution of the species distribution model overlap statistic I created from 100 replicates of Maxent models that compared randomly selected lesser prairie-chicken (*Tympanuchus pallidicinctus*) locations from the aerial survey dataset to locations from the eBird dataset. The empirical I statistic (indicated by an arrow) represents the empirical overlap statistic estimated from the actual occurrence data for each data set. Aerial survey and eBird occurrence data were collected from March 15-May 15, 2012-2014.

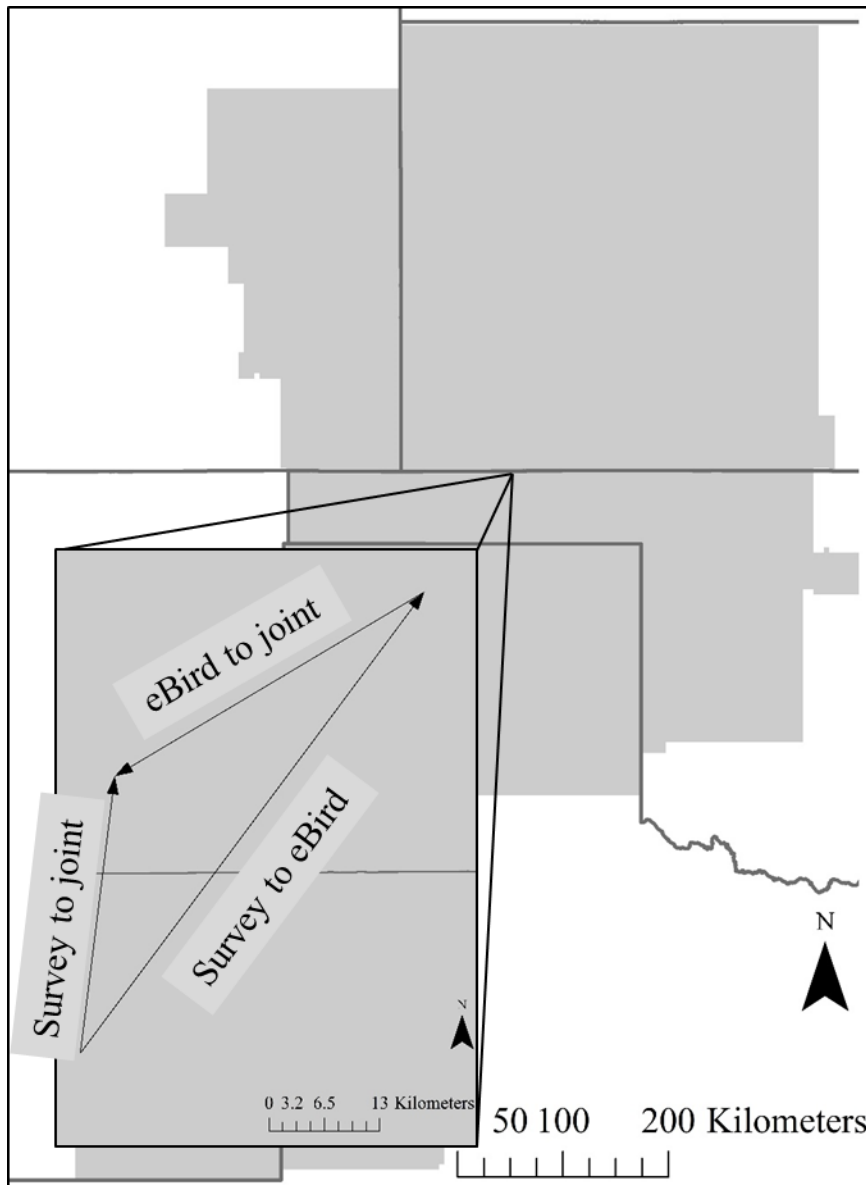


Figure 1.3. Estimates of centroid shifts between Maxent models for the lesser prairie-chicken (*Tympanuchus pallidicinctus*) as determined by three occurrence datasets; aerial survey, eBird, and joint (combined aerial survey and eBird). Data were collected from March 15-May 15, 2012-2014. Shifts were estimated as 67.56 km from the survey to eBird model, 42.25 km from the eBird to joint model, and 32.81 km from the survey to joint model.

Table 1.2. Akaike's Information Criterion (AIC) model selection results for Maxent model performance of three lesser prairie-chicken (*Tympanuchus pallidicinctus*) occurrence datasets based on different regularization multiplier values. Top performing models are bolded for each occurrence dataset.

Regularization multiplier	Aerial survey		eBird		Joint	
	AIC score	Log Likelihood	AIC score	Log Likelihood	AIC score	Log Likelihood
0.25	1329.80	-632.90	1318.00	-638.00	1358.23	-637.12
0.5	1320.80	-636.40	1324.34	-644.17	1339.66	-640.83
1	1307.87	-634.94	1325.82	-644.91	1325.36	-640.68
1.5	1303.13	-636.57	1324.97	-643.48	1340.47	-648.23
2	1314.76	-643.38	1322.90	-645.45	1327.66	-646.83
4	1326.52	-650.26	1331.95	-657.98	1331.12	-657.56
6	1323.29	-655.64	1330.78	-661.39	1342.39	-667.19
8	1334.84	-660.42	1335.38	-664.69	1342.93	-666.47
10	1335.04	-663.52	1335.58	-664.79	1342.21	-669.11

All three final models for each occurrence dataset exhibited idiosyncratic relationships between the probability of suitability and the environmental layers included in our analyses (Figures 1.4-1.6; Table 1.1). However, across all model sets, existing vegetation cover (EVC) and existing vegetation height (EVH) were consistently the two most important variables to models, with EVC contributing >50% to model accuracy gain for survey and eBird models (Table 1.3). Thus, regardless of occurrence datasets, vegetation cover and height were the primary drivers of the LPC distribution and out-contributed anthropogenic influences at a 5 km grain. We note that in Figures 1.4-1.6, only categories that had estimated lambdas across 75% of all model replications (Table 1.4) are graphically represented for simplicity.

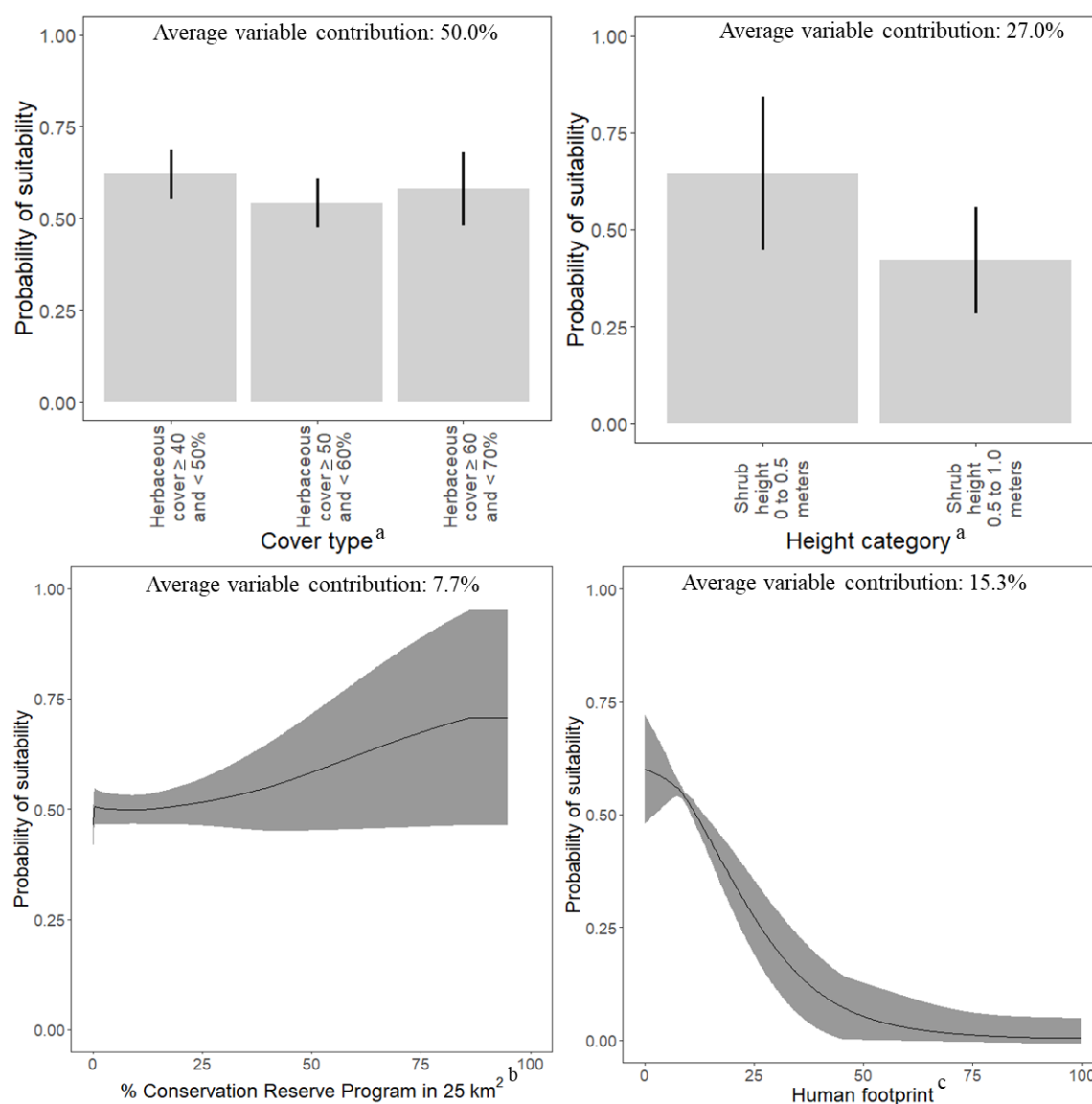


Figure 1.4. Relationship between environmental^a variables and probability of suitability (and associated standard deviation bars) for the lesser prairie-chicken (*Tympanuchus pallidicinctus*) as estimated through Maxent using occurrence data from aerial surveys from March 15-May 15, 2012-2014. Response curves indicate mean response of 100 replicated Maxent runs and the \pm one standard deviation. Average variable contribution to Maxent model accuracy gain is indicated in each panel.

^a Detailed descriptions of cover types and height categories can be found at <https://www.landfire.gov/documents/LF-GAPMapUnitDescriptions.pdf> (accessed 9/4/2019).

^b Percentage of area (%) enrolled in the Conservation Reserve Program (CRP) as reported by the United States Department of Agriculture in 2014 (unpublished data).

^c Represents human population pressure, land use, infrastructure, and access into one continuous data set ranging from 0 – 100 where 0 is no impact and 100 is maximum impact (Columbia University 2005).

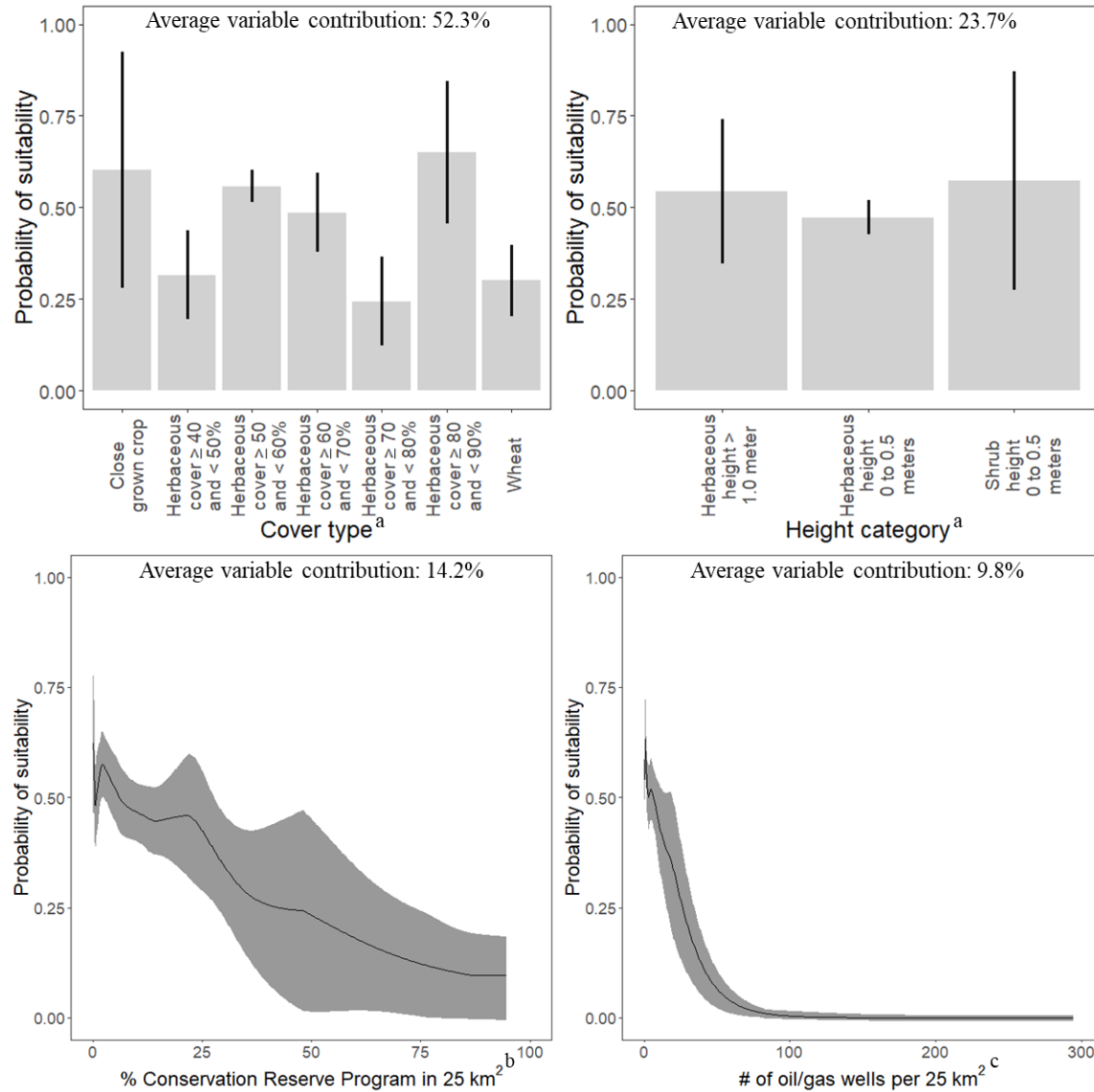


Figure 1.5. Relationship between environmental variables and probability of suitability (and associated standard deviation bars) for the lesser prairie-chicken (*Tympanuchus pallidicinctus*) as estimated through Maxent using occurrence data from the eBird dataset from March 15-May 15, 2012-2014. Response curves indicate mean response of 100 replicated Maxent runs and the \pm one standard deviation. Average variable contribution to Maxent model accuracy gain is indicated in each panel.

^a Detailed descriptions of cover types and height categories can be found at <https://www.landfire.gov/documents/LF-GAPMapUnitDescriptions.pdf> (accessed 9/4/2019).

^b Percentage of area (%) enrolled in the Conservation Reserve Program (CRP) as reported by the United States Department of Agriculture in 2014 (unpublished data).

^c Provided by IHS Market (<https://ihsmarkit.com/products/us-oil-gas-spatial-layers.html>).

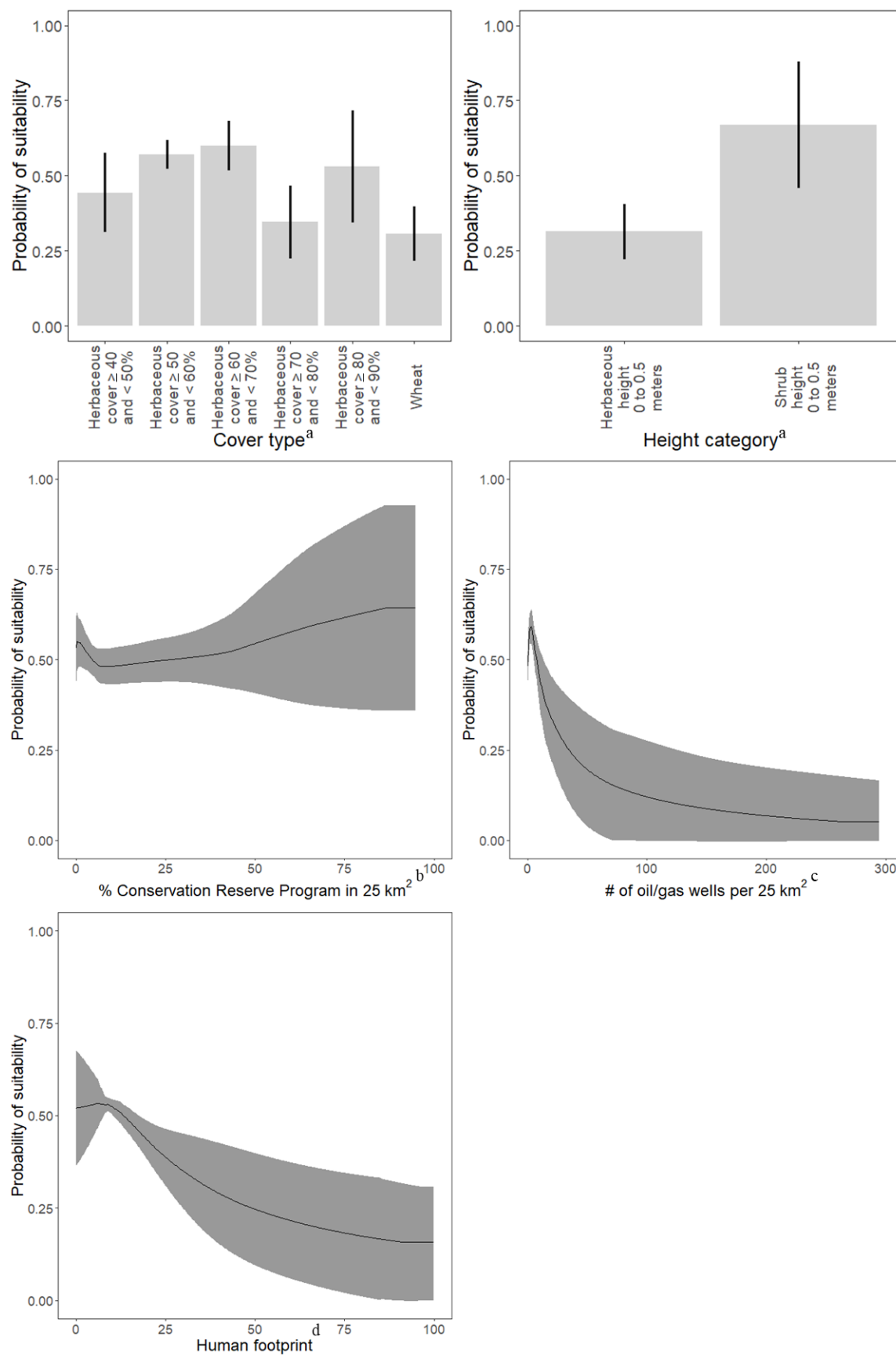


Figure 1.6. Relationship between environmental variables and probability of suitability (and associated standard deviation bars) for the lesser prairie-chicken (*Tympanuchus pallidicinctus*) as estimated through Maxent using occurrence data from combined aerial survey/eBird data from March 15-May 15, 2012-2014. Response curves indicate mean response of 100 replicated Maxent runs and the +/- one standard deviation. Average variable contribution to Maxent model accuracy gain is indicated in each panel.

^a Detailed descriptions of cover types and height categories can be found at <https://www.landfire.gov/documents/LF-GAPMapUnitDescriptions.pdf> (accessed 9/4/2019).

^b Percentage of area (%) enrolled in the Conservation Reserve Program (CRP) as reported by the United States Department of Agriculture in 2014 (unpublished data).

^c Provided by IHS Market (<https://ihsmarkit.com/products/us-oil-gas-spatial-layers.html>).

^d Represents human population pressure, land use, infrastructure, and access into one continuous data set ranging from 0 – 100 where 0 is no impact and 100 is maximum impact (Columbia University 2005).

Table 1.3. Average estimates of variable contribution^a to model accuracy gain for three Maxent model sets of lesser prairie-chicken (*Tympanuchus pallidicinctus*) environmental suitability created using observations from eBird data, recorded in aerial surveys, and a model combining both datasets from March 15-May 15, 2012-2014.

Location type	Occurrence locations (<i>n</i>)	Average contribution (%)				
		CRP ^b	EVC ^c	EVH ^d	HF ^e	WELLS ^g
Aerial survey	68	7.7 (6.5-8.9)	50.0 (47.6-52.4)	27.0 (24.6-29.5)	15.3 (13.8-16.7)	0.00
eBird	68	14.2 (12.6-15.8)	52.3 (50.5-54.1)	23.7 (22.1-25.3)	0.00	9.8 (8.7-10.9)
Joint	68	12.8 (10.9-14.6)	44.3 (42.0-46.6)	24.6 (22.6-26.5)	7.9 (6.6-9.3)	10.4 (9.1-11.8)

^a 95% confidence intervals are indicated in parentheses.

^b Percent cover of the Conservation Reserve Program per 25 km².

^c Existing vegetation cover.

^d Existing vegetation height.

^e Represents human population pressure, land use, infrastructure, and access into one continuous data set ranging from 0 – 100 where 0 is no impact and 100 is maximum impact (Columbia University 2005).

^f Number of oil and gas wells per 25km².

Table 1.4. Mean beta coefficients and standard deviations (SD) for the two categorical environmental variables for Maxent models using three different lesser prairie-chicken (*Tympanuchus pallidicinctus*) datasets: eBird, aerial survey, and a combination of the two (joint). Lesser prairie-chicken locations were collected from March 15-May 15, 2012-2014.

Variable	Aerial survey			eBird			Joint		
	n^a	$\bar{\beta}$	SD	n^a	$\bar{\beta}$	SD	n^a	$\bar{\beta}$	SD
Existing vegetation cover									
Close grown crop	0	-	-	76	3.93	0.45	48	2.82	0.38
Herbaceous cover ≥ 40 and $< 50\%$	100	1.46	0.45	95	1.92	0.56	91	0.86	0.58
Herbaceous cover ≥ 50 and $< 60\%$	100	1.21	0.45	100	2.94	0.41	100	1.42	0.42
Herbaceous cover ≥ 60 and $< 70\%$	98	1.23	0.50	99	2.65	0.46	98	1.47	0.45
Herbaceous cover ≥ 70 and $< 80\%$	55	-0.001	0.55	92	1.69	0.63	77	0.57	0.61
Herbaceous cover ≥ 80 and $< 90\%$	0	-	-	93	3.70	0.54	82	1.49	0.63
Row crop	46	-0.23	0.49	0	-	-	36	-0.53	0.41
Shrub cover ≥ 10 and $< 20\%$	0			55	3.71	0.42	0	-	-
Shrub cover ≥ 50 and $< 60\%$	52	0.58	0.37	0	-	-	41	0.73	0.37
Wheat	55	-0.41	0.45	99	1.86	0.52	82	0.48	0.45
Existing vegetation height									
Barren	45	2.89	0.74	0	-	-	0	-	-
Herbaceous height 0 to 0.5 meters	0	-	-	99	1.40	0.54	88	0.64	0.46
Herbaceous height 0.5 to 1.0 meters	19	0.01	0.40	68	1.02	0.68	29	-0.22	0.26
Herbaceous height > 1.0 meter	23	0.52	0.42	90	1.48	0.69	65	0.74	0.45
Shrub height 0 to 0.5 meters	83	2.19	0.81	75	3.92	0.69	80	2.69	0.71
Shrub height 0.5 to 1.0 meters	75	1.14	0.60	0	-	-	66	0.91	0.58

^a Number of model replicates (out of 100 total) in which this category had an estimated beta coefficient.

Within the categorical variable EVC, 25 km² landscape matrices dominated by 40-69% herbaceous cover had a strong positive association with LPC environmental suitability across model sets based on lambdas ($\beta \geq 0.86$, SD = 0.58 and ≤ 2.94 , SE = 0.41, Table 1.4). There was a positive relationship with matrices dominated by close grown crops and wheat in the eBird model ($\beta = 3.93$, SD = 0.45 and 1.86, SD = 0.52, respectively) and joint model ($\beta = 2.82$, SD = 0.38 and 0.48, SD = 0.45, respectively). Conversely, the close grown crop category was not included in any model replicates for the aerial survey model set while matrices dominated by wheat had a negative influence on site suitability based on this model set ($\beta = -0.41$, SD = 0.45; Table 1.4). Finally, there was a strong positive relationship with matrices dominated by 10-19% shrub cover for the eBird model ($\beta = 3.71$, SD = 0.42) whereas a positive relationship with matrices dominated by 50-59% shrub cover existed in the aerial survey ($\beta = 0.58$, SD = 0.37) and joint models ($\beta = 0.73$, SD = 0.37).

Within EVH, matrices dominated by shrub heights of 0-0.5 m were positively associated with LPC environmental suitability across all model sets ($\beta \geq 2.19$, SD = 0.81 and ≤ 3.92 , SD = 0.69; Table 1.4) whereas matrices dominated by shrub heights of 0.5 to 1 m positively influenced suitability in the aerial survey and joint models. Landscape matrices dominated by herbaceous height of > 1 m had a significant positive influence on site suitability for LPCs across all model sets ($\beta \geq 0.52$, SD = 0.42 and ≤ 1.48 , SD = 0.69). However, matrices dominated by herbaceous height of ≤ 1 m in height was only influential in eBird and joint models (Table 1.4). Matrices dominated by barren lands were shown to have a positive relationship in the aerial survey model ($\beta = 2.89$, SD = 0.74; Table 1.4), likely representing areas indicative of leks.

Similar to our categorical variables, our models exhibited both agreement and disagreement in the relationships between LPC occurrences and continuous environmental variables (Figures 1.4-1.6). For instance, 25 km² landscape matrices with higher densities of oil/gas wells and a greater human imprint consistently had lower probability of suitability values for LPCs. Conversely, the relationship between LPC suitability and the % of CRP within 25 km² matrices was disparate among the eBird model when compared to the aerial survey and joint models (Figures 1.4-1.6).

Roadside Bias

The eBird occurrence locations were significantly biased towards roads within 250 m (road bias = 2.13) whereas the aerial survey locations were significantly biased away from roads (road bias = -5.78). However, when we combined both the eBird and the aerial survey data sets, we did not detect a roadside bias (road bias = 1.07).

Results from our correlation analysis indicated that road density was not highly correlated with the oil/gas well ($r = 0.03$), the human footprint ($r = 0.53$), or the CRP ($r = 0.07$) environmental layers. However, we did detect differences in road density across matrices dominated by different cover types ($p < 0.01$; Figure 1.7) and height categories ($p < 0.01$; Figure 1.8). Landscape matrices dominated by close grown crops had the highest road density of any cover types (1.16 km/25 km², SE = 0.09) and matrices dominated by row crops (0.95 km/25 km², SE = 0.01) and wheat (0.94 km/25 km², SE = 0.01) also had significantly greater road densities than herbaceous and shrub cover types (Figure 1.7). Matrices dominated by herbaceous height > 1 m

had the highest amount of road density among height categories (1.05 km/km^2 , $\text{SE} = 0.03$) whereas landscape matrices dominated by shrub height of 0 to 0.5 m (0.24 km/km^2 , $\text{SE} = 0.03$) and shrub height of 0.5 to 1 m (0.32 km/km^2 , $\text{SE} = 0.02$) had the lowest amounts of road density (Figure 1.8).

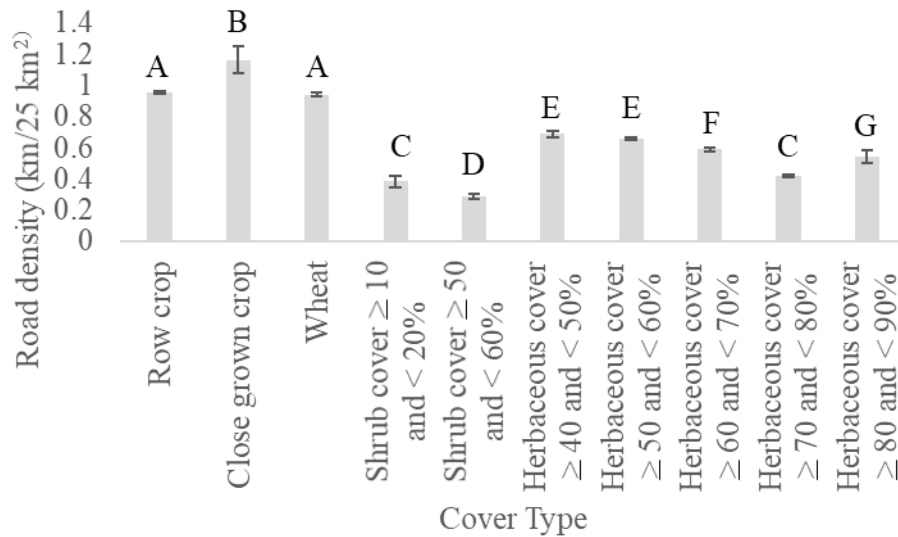


Figure 1.7. Difference in road density^a by existing vegetation cover (EVC)^b type through the lesser prairie-chicken's (*Tympanuchus pallidicinctus*) distribution as determined by a Kruskal-Wallis test. Letters represent significance categories as determined by a Tukey's Multiple Comparison Test.

^a Road GIS layers were obtained for Colorado (<https://data.colorado.gov/>), Kansas (<https://www.kansasgis.org/>), New Mexico (<http://rgis.unm.edu/>), Oklahoma (<http://gis-okdot.opendata.arcgis.com/>), and Texas (<http://gis-txdot.opendata.arcgis.com/>) which represented the five states within the LPC's distribution.

^b Detailed descriptions of cover types and height categories can be found at <https://www.landfire.gov/documents/LF-GAPMapUnitDescriptions.pdf> (accessed 9/4/2019).

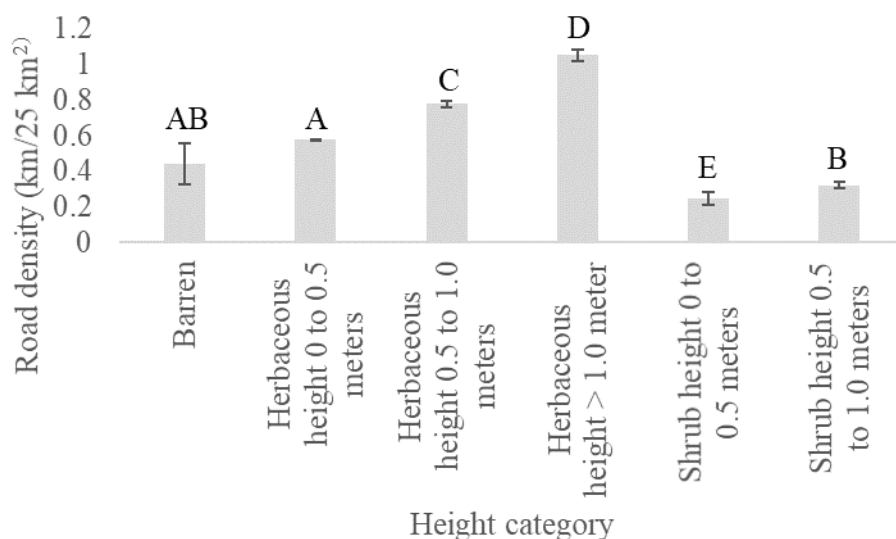


Figure 1.8 Difference in road density^a by existing vegetation height (EVH)^b categories through the lesser prairie-chicken's (*Tympanuchus pallidicinctus*) distribution as determined by a Kruskal-Wallis test. Letters represent significance categories as determined by a Tukey's Multiple Comparison Test.

^a Road GIS layers were obtained for Colorado (<https://data.colorado.gov/>), Kansas (<https://www.kansasgis.org/>), New Mexico (<http://rgis.unm.edu/>), Oklahoma (<http://gis-okdot.opendata.arcgis.com/>), and Texas (<http://gis-txdot.opendata.arcgis.com/>) which represented the five states within the LPC's distribution.

^b Detailed descriptions of cover types and height categories can be found at <https://www.landfire.gov/documents/LF-GAPMapUnitDescriptions.pdf> (accessed 9/4/2019)

OBJECTIVE 2 – Determine the potential of areas of high conservation value for lesser prairie-chickens on secondary species of management value

METHODS

Study site

We conducted our study in Beaver County, Oklahoma (36° 45' N, 100° 23' W). The county is dominated by sand sagebrush (*Artemisia filifolia*) shrublands and land actively enrolled in CRP (31.5% of the county) that varied in composition but frequently included old world bluestem (*Bothriochloa ischaemum*), sideoats grama (*Bouteloua curtipendula*), western wheatgrass (*Elymus smithii*), and Illinois bundleflower (*Desmanthus illinoensis*). Planted pastures were often areas where the CRP contract had not been renewed or where old world bluestem had been planted and managed for cattle grazing. Shortgrass prairie vegetation included blue grama (*Bouteloua gracilis*), buffalograss (*Bouteloua dactyloides*), sideoats grama, soapweed yucca (*Yucca glauca*), and sand sagebrush. Cropland was primarily planted to winter wheat (*Triticum* spp.), but also included small amounts of sorghum (*Sorghum bicolor*) and corn (*Zea mays*). The Beaver River flows west to east through Beaver County and most of the county's woodland vegetation, consisting primarily of eastern cottonwood (*Populus deltoids*) and non-native, invasive salt cedar (*Tamarix* spp.), can be found along it.

Our study sites in Beaver County contained 4 primary types of anthropogenic features: roads, power lines, oil and gas wells, and residential areas. We used the US Department of Agriculture's (USDA) GeoSpatial Data Gateway website to access the TIGER shapefile (produced by the US Census Bureau) depicting the primary and secondary roads of Beaver County. We did not differentiate between road types (paved/unpaved) in our analysis. Residential areas were mapped by hand in ArcMap 10.1 (ESRI 2011, Redlands, CA) using the 2013 USDA National Agriculture Imagery Program imagery as a guideline for Beaver County. We obtained the location of power lines and active oil and gas wells from the Western Association of Fish and Wildlife Agencies.

Occurrence location data

Lesser prairie-chicken locations

We used occurrence locations for LPC distribution models from GPS locations acquired during part of a larger research project. Our study was centered on 3 LPC leks which were spaced approximately 32 km apart in the northern, southwestern, and southeastern regions of the county. We trapped 32 female and 72 male LPCs from March to May 2013-2015 on lek sites primarily during the spring using methods approved by Oklahoma State University's Institutional Animal Care and Use Committee under protocol #AG-13-3. We used 20-25 walk-in funnel traps (per lek) arranged strategically around lek sites (Haukos et al. 1990). Captured birds were sexed, aged (Copelin 1963), and banded with a numbered, aluminum band (Hagen et al. 2007). We fit a 22 gram, solar, GPS transmitter to both male and female LPCs just above the pelvis of the bird (a "rump mount") using a lightweight, Teflon harness (Bedrosian and Craighead 2007). Transmitters were constructed by Microwave Telemetry Inc. (Columbia, MD) and programed to

collect as many as 15 locations in a 24-hour period, including at least two nocturnal locations. The minimum interval between locations was 1 hour. The horizontal error associated with our transmitters was ± 18 m with 85% of locations falling below an 18 m circular error (Ted Rollins, Microwave Telemetry, personal communication). We censored locations collected in the first 2 weeks after capture to account for the potential effects of capture myopathy.

Northern bobwhite (Colinus virginianus) and scaled quail (Callipepla squamata) locations

For northern bobwhite and scaled quail occurrence locations, we used radio-telemetry data that was collected as part of a larger research project. We captured bobwhite and scaled quail annually from 2013-2015 using walk-in funnel traps (Stoddard 1931). Captured birds were fitted with a necklace-style radio-transmitter weight 6 g (Advanced Telemetry Systems, Inc., Isanti, Minnesota) if they met a minimum mass requirement of 130 g. We located radio-marked individuals a minimum of three times per week using a scanning receiver and a Yagi antenna by homing within 15 m and recording the distance and azimuth to the quail location. To capture diurnal variability in habitat use patterns, we tracked quail to different times of the day on subsequent days. All trapping and handling methods complied with the protocol determined by Oklahoma State University's Institutional Animal Care and Use Committee Permit (no. AG-11-22).

Additional data and spatial rarefaction of location data

In addition to the occurrence locations obtained from GPS and radio-telemetry data, we also collated locations from the Biodiversity Information Serving Our Nation (BISON) data base (<https://bison.usgs.gov/>), which was created by the USGS and provides a platform to access collated species occurrence data from multiple research data sets throughout the United States. We obtained occurrence data from our three study species from 2013-2015 from the BISON website to increase the spatial coverage of our occurrence locations.

As per our methods in Objective 1, once GPS, radio-telemetry, and BISON occurrence locations were collated for all three species, we used the spatial rarefaction tool in SDMtoolbox (Brown 2014) to reduce spatial auto-correlation of our location data for all three species in ArcGIS 10.2 (ESRI, Redlands, CA). We used daily movement information to determine the intraspecific spatial rarefaction distance for each dataset. For LPCs, we used a spatial rarefaction distance of 293 m (Unger 2017), whereas a distance of 179 m and 214 m were used for bobwhite and scaled quail, respectively (Tanner et al. 2019).

Environmental data

As we were interested in small-scale variability in vegetation patterns associated with changing environmental conditions (i.e., annual precipitation), we used environmental layers associated with the Rangeland Analysis Platform (RAP; Jones et al. 2018). This dataset provides annual percent cover of different functional cover groups (Table 2.1) which are estimates produced from combining field data associated with the NRCS National Resources Inventory and the BLM Assessment, Inventory, and Monitoring datasets with Landsat satellite imagery, abiotic land surface data, and gridded meteorology data within a Random Forest model (Table 2.1; Jones et

al. 2018). The resulting model predicts the annual percent cover of these functional cover groups at a 30 m resolution. To match the temporal extent of our location data, we obtained rasters for each cover class from 2013-2015. Finally, we also included a spatially explicit active CRP raster, which was provided by the USDA Farm Service Agency.

Table 2.1. Average annual changes in the percent cover of plant functional groups and annual precipitation in Beaver County, Oklahoma from 2013-2015 as determined by the Rangeland Analysis Platform^a.

Year	Annual forb & grass cover (%)	Perennial forb & grass cover (%)	Shrub cover (%)	Bare ground cover (%)	Tree cover (%)	Annual precipitation (cm)
2013	10.95	44.18	7.05	21.19	1.23	48.59
2014	10.14	51.97	6.7	18.72	1.38	44.22
2015	16.05	61	8.14	9.04	2.7	84.89

^aJones et al. 2018.

To incorporate the influence of anthropogenic features into our distribution models, we created distance-based rasters to anthropogenic features. The anthropogenic rasters included in our analysis were distance to oil/gas wells, power lines, residential areas, roads, and vertical structures (i.e., wind turbines, cell phone towers, ec.). We obtained the location of oil/gas wells, power lines, and vertical structures from the Western Associated of Fish and Wildlife Agencies. We obtained a roads layer through the USDA GeoSpatial Data Gateway to access the TIGER shapefile depicting primary and secondary roads throughout the county. Finally, we obtained residential area data by hand mapping these locations in ArcGIS 10.2 using 2013 USDA NAIP imagery within Beaver county. Once all spatially explicit anthropogenic feature data were obtained, we created a Euclidean distance-based raster for each feature type at a 30 m resolution to match the spatial grain of the RAP rasters.

Finally, we obtained a digital elevation model (DEM) through the USGS National Map Data Collection (<https://catalog.data.gov/dataset/usgs-national-elevation-dataset-ned-1-meter-downloadable-data-collection-from-the-national-map->) and used the Spatial Analyst tool in ArcGIS 10.2 to calculate the aspect and slope layers. Thus, our initial environmental layer data set included 15 variables per year (seven vegetation, five anthropogenic, and three geographic layers). We note that only the RAP vegetation related variables were temporally dynamic in our distribution models, while the anthropogenic and geographic variables remained static.

Data analysis

All species distribution models were created following identical methods as described in the Methods section for Objective 1. However, we only used the AUC and test omission metrics to assess model performance and reduced the number of model replicates from 100 to 30 for simplicity. As our objective for this specific study was to assess how areas of multi-species overlap varied with temporal variability in environmental conditions, we calculated two metrics of overlap based on the logistic output from our Maxent models and from discrete binary maps (either suitable or non-suitable based on a suitability threshold). For the logistic probability maps, we compared the niche similarity of the three species for each year (2013-2015) using the *I* statistic in ENMTools as described above in Objective 1 (Warren et al. 2010). For the binary maps, we calculated the range overlap value in ENMTools, which is estimated as $(N_{x,y}/\min(N_x, N_y))$, where $N_{x,y}$ is the number of pixels in which both species are predicted to be present and N_x and N_y are the number of pixels where species X and species Y are predicted present, respectively (Warren et al. 2010). Because this metric is reliant on a suitability threshold, we estimated the range overlap for all values of the suitability threshold, ranging from 0.01 to 1 (i.e., 99 estimates).

Post-hoc analysis

We created discrete maps of suitable and non-suitable areas for each species using the maximum sensitivity and specificity threshold rule (Liu et al. 2013). Once these discrete output maps were created, we used the Raster Calculator tool in ArcGIS 10.2 to estimate areas with four possible categories: suitable for an individual species (two possible categories), areas suitable for two species, and areas in which our models predicted to be unsuitable for both species for each year.

We then calculated means of all environmental variables contained in each one of these discrete map categories by extracting raster values to points centered on each pixel. Once these values were extracted for each map category, we used nonmetric multidimensional scaling (NMDS) using the “vegan” package (Oksanen et al. 2015) in Program R to visualize differences in environmental layers across all four possible categories for each species/year combination (i.e., northern bobwhite/LPC, scaled quail/LPC, and northern bobwhite/scaled quail for 2013, 2014, and 2015). Our data set was comprised of different types of variables on different scales (i.e., distance-based, percentage based, etc.), thus we used Gower distance coefficients to create a dissimilarity matrix (Gower 1971). For all three NMDS analyses (i.e., species combinations), we used two axes to estimate ordinal space as this approach simplified the visualization and produced well-performing stress values (Oksanen et al. 2015). Finally, we tested for significant differences in ordinal space associated with different map categories and across all three years using a permutational multivariate analysis of variance (PERMANOVA) with 10,000 permutations (Oksanen et al. 2015).

RESULTS

From 1 April 2013- 1 July 2015, we obtained a total of 13,555 northern bobwhite locations (2013 = 6,601, 2014 = 5,675, 2015 = 1,279) from 400 radio-collared individuals. We obtained a total of 7,120 scaled quail locations (2013 = 3,204, 2014 = 3,117, 2015 = 799) from 194 radio-collared individuals. Finally, we obtained 120,231 LPC locations (2013 = 53,099, 2014 = 59,116, 2015 = 8,016) from 67 GPS-transmitted individuals. Data acquisition from the BISON data base further provided 160, 45, and 1 additional occurrence locations for northern bobwhite, scaled quail, and LPC, respectively. After spatial rarefaction, our final occurrence data sets included 933 northern bobwhite locations (2013 = 434, 2014 = 402, 2015 = 97), 507 scaled quail locations (2013 = 228, 2014 = 212, 2015 = 67), and 887 LPC locations (2013 = 296, 2014 = 441, 2015 = 150).

Based on AIC_c values, regularization multiplier values of 0.50 (2013), 0.25 (2014), and 0.25 (2015) were used for LPC models, values of 1.50 (2013), 1.50 (2014), and 1 (2015) were used for northern bobwhite models, and a value of 1 was used for all scaled quail models. All model performance metrics indicated good performance of our species distribution models, with all average test AUC values being ≥ 0.87 and all average test omission error values being ≤ 0.22 (Table 2.2). All models indicated idiosyncratic relationships between the probability of suitability and environmental variables across the environmental variables included. However, elevation was included as a primary contributor to model accuracy gain in all species distribution models (Table 2.3). For the LPC, the CRP cover class was a primary contributing variable to model accuracy gain as well, contributing $>31\%$ across all three years. When CRP was present on the landscape, the probability of suitability for the LPC was 74.27% (SE = 0.001), 74.68% (SE = 0.002), and 75.05% (SE = 0.006) during 2013, 2014, and 2015, respectively. Conversely, areas not comprised of CRP cover had a probability of suitability for LPCs of 27.58% (SE = 0.04), 29.30% (SE = 0.04), and 23.73% (0.06) during 2013, 2014, and 2015, respectively (Figure 2.1). This indicated that areas in CRP were predicted to be 2.69, 2.55, and 3.16 times more

suitable for LPCs than areas outside of CRP. However, CRP was not a contributing variable in any northern bobwhite or scaled quail distribution models.

Table 2.2. Average estimates of model performance for 30 replicates of Maxent models of the lesser prairie-chicken (*Tympanuchus pallidicinctus*), northern bobwhite (*Colinus virginianus*), and scaled quail (*Callipepla squamata*) in Beaver County, Oklahoma from April 1, 2013-July 1, 2015. AUC^b values > 0.75 indicate good model performance; lower test omission error values are associated with higher model performance.

Species	Year	Average test AUC ^a	Average test omission error
Lesser prairie-chicken	2013	0.87	0.22
	2014	0.88	0.15
	2015	0.91	0.12
Northern bobwhite	2013	0.94	0.09
	2014	0.93	0.08
	2015	0.88	0.15
Scaled quail	2013	0.88	0.05
	2014	0.94	0.07
	2025	0.95	0.06

^a Area under the curve of the receiver operating characteristic.

Table 2.3. Average estimates of variable contribution^a to model accuracy gain for 30 replicates of Maxent models of the lesser prairie-chicken (*Tympanuchus pallidicinctus*), northern bobwhite (*Colinus virginianus*), and scaled quail (*Callipepla squamata*) in Beaver County, Oklahoma from April 1, 2013-July 1, 2015.

Species	Year	Cover of annual forbs and grass (%) ^b	Cover of bare ground (%) ^b	Cover of litter (%) ^b	Cover of perennial forbs and grass (%) ^b	Cover of shrubs (%) ^b	Cover of trees (%) ^b	CRP ^c	Elevation (m)	Distance to power lines (m)	Distance to roads (m)
Lesser prairie- chicken	2013	9.53 (0.43)	20.59 (0.89)	-	-	-	-	31.42 (0.92)	38.47 (0.57)	-	-
	2014	8.93 (0.49)	-	9.43 (0.29)	-	-	-	32.16 (0.74)	49.48 (0.75)	-	-
	2015	-	-	-	8.44 (0.85)	7.35 (0.78)	-	34.61 (1.18)	49.60 (0.80)	-	-
Northern bobwhite	2013	-	-	-	10.86 (0.29)	8.53 (0.27)	-	-	34.58 (0.53)	-	46.03 (0.74)
	2014	11.42 (0.43)	-	-	-	40.42 (0.96)	-	-	21.68 (0.61)	-	26.78 (0.63)
	2015	-	-	-	15.66 (2.26)	-	20.46 (3.25)	-	41.39 (4.34)	12.75 (3.91)	9.74 (4.26)
Scaled quail	2013	-	-	-	-	-	-	-	91.43 (0.52)	8.57 (0.52)	-
	2014	11.85 (2.23)	-	-	-	34.23 (3.35)	-	-	44.59 (2.43)	9.33 (1.54)	-
	2015	-	8.56 (2.15)	-	-	-	25.10 (3.21)	-	55.00 (2.30)	11.34 (2.59)	-

^aStandard errors included in parentheses.

^bDetermined through the Rangeland Analysis Platform (Jones et al. 2018)

^cConservation Reserve Program

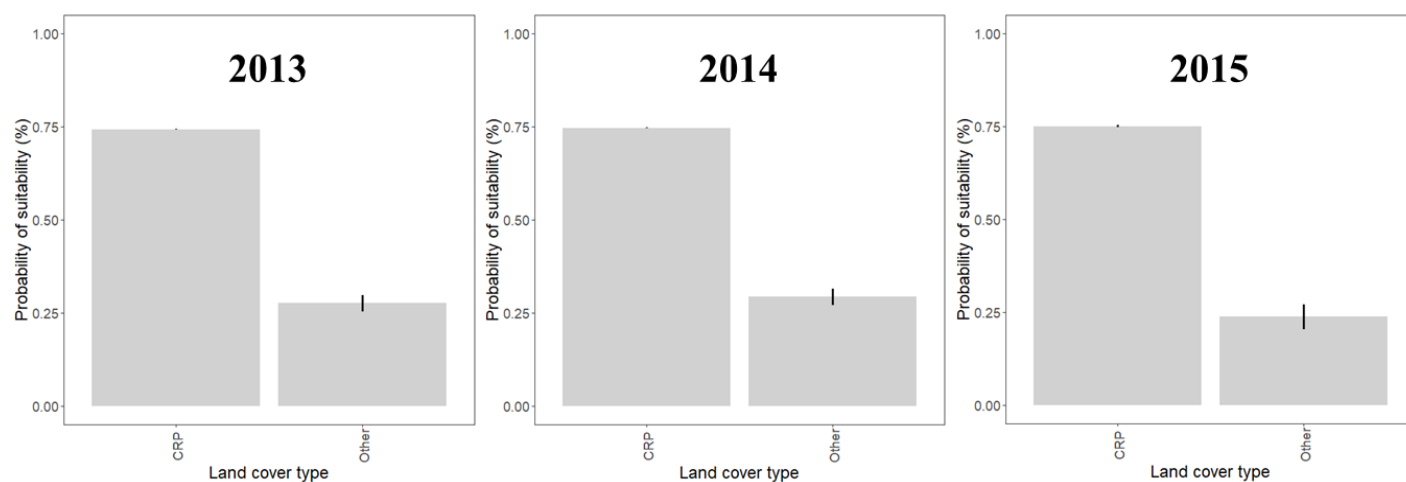


Figure 2.1. Probability of environmental suitability for the lesser prairie-chicken (*Tympanuchus pallidicinctus*) in relation to whether or not the land cover type was actively enrolled in the Conservation Reserve Program (CRP). Probability of suitability was determined by 30 replicated Maxent models in Beaver County, Oklahoma from April 1, 2013-July 1, 2015.

All binary maps derived from the logistic outputs of our species distribution models indicated that the probability of niche overlap for LPC with northern bobwhite or scaled quail was greatest during 2013 (Figures 2.2 and 2.3), corresponding to the period of greater drought and lower rainfall (compared to 2014 and 2015). Conversely, the amount of area predicted as suitable for both northern bobwhite and scaled quail was similar across years, despite a greater amount of area being predicted suitable for scaled quail during 2013 (Figure 2.4). Based on our estimates of the *I* statistic, niche similarity was lowest between northern bobwhite and LPC, ranging from 0.63 in 2013 to 0.40 in 2015 (Figure 2.5). Similarly, niche similarity between scaled quail and LPCs was greatest in 2013 and lowest in 2015, whereas there was little change in the niche similarity estimates between northern bobwhite and scaled quail across years (Figure 2.5). When assessing range overlap values across years and logistic thresholds, we predicted higher amounts of range overlap for northern bobwhite and LPCs and scaled quail and LPCs during 2013 when compared to 2014-2015. The higher range overlap values for northern bobwhite and scaled quail varied across years and varied across logistic thresholds, in which 2013 and 2015 had similar amounts of range overlap up to a logistic threshold of 0.23, but diverged at higher threshold values in which 2015 indicated greater amounts of range overlap (Figure 2.6).

Post-hoc results

All NMDS models performed well with two explanatory axes based on stress tests (northern bobwhite/LPC: 0.11, northern bobwhite/scaled quail: 0.03, and scaled quail/LPC: 0.10). PERMANOVA results indicated significant differences in ordinal space associated with discrete map categories for the northern bobwhite/LPC comparison ($R^2 = 0.68$, $P = 0.001$), the northern bobwhite/scaled quail comparison ($R^2 = 0.67$, $P = 0.004$), and the scaled quail/LPC comparison ($R^2 = 0.62$, $P = 0.002$). PERMANOVA analyses assessing differences across years within each map category indicated significant differences across all three years for the northern bobwhite/scaled quail comparison ($R^2 = 0.40$, $P = 0.05$) and the scaled quail/LPC comparison ($R^2 = 0.40$, $P = 0.03$), but not for the northern bobwhite/LPC comparison ($R^2 = 0.32$, $P = 0.11$).

Across both NMDS models with LPC comparisons, the x-axis (NMDS1) generally represented relationships with anthropogenic features (greater values being closer to anthropogenic features), whereas the y-axis (NMDS2) represented changes in functional vegetation cover types, with high values represented by woody cover and lower values represented bare areas. For all comparisons with LPCs, areas estimated as suitable for only LPCs contained greater amounts of CRP when compared to all other map categories. Areas estimated as suitable for only LPCs had an average CRP coverage of 29.1-41.8% whereas areas estimated as suitable for only northern bobwhite or scaled quail had a CRP coverage of <1%. Similarly, areas predicted suitable for only LPCs generally were further away from anthropogenic features when compared to areas predicted suitable for only northern bobwhite and scaled quail (Figures 2.7 and 2.8).

Conversely, the x-axis for the NMDS model assessing northern bobwhite and scaled quail suitability models represented anthropogenic features but the y-axis was inverse, in which low NMDS2 values represented woody cover and high values represented areas with little-to-no vegetation (Figure 2.9). This model indicated that areas predicted suitable for only scaled quail had greater CRP coverage than areas predicted only suitable for northern bobwhite or areas in

which both northern bobwhite and scaled quail were predicted present. However, the greatest amount of CRP cover in these areas was 12.7% and was similar to values within the areas where neither species was predicted present. Instead, divergence between these species occurred because of differences in the distance to anthropogenic features, in which areas predicted suitable for northern bobwhite were closer to anthropogenic features than areas predicted suitable for only scaled quail (Figure 2.9).

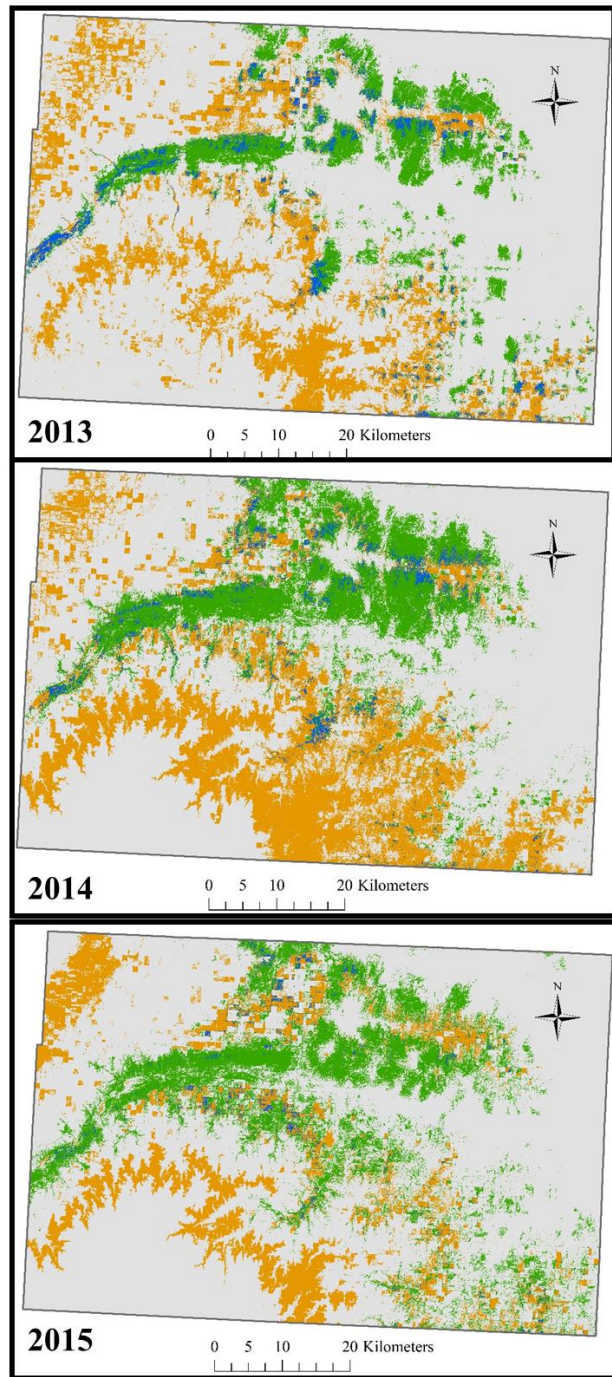


Figure 2.2. Binary suitability output maps for the lesser prairie-chicken (*Tympanuchus pallidicinctus*) and northern bobwhite (*Colinus virginianus*) as predicted by 30 replicated Maxent models in Beaver County, Oklahoma from April 1, 2013-July 1, 2015. Green indicates areas predicated suitable for northern bobwhite only, orange for lesser prairie-chicken only, blue for both species, and grey for neither species. Binary maps were created from logistic probability outputs using the maximum sensitivity and specificity threshold rule.

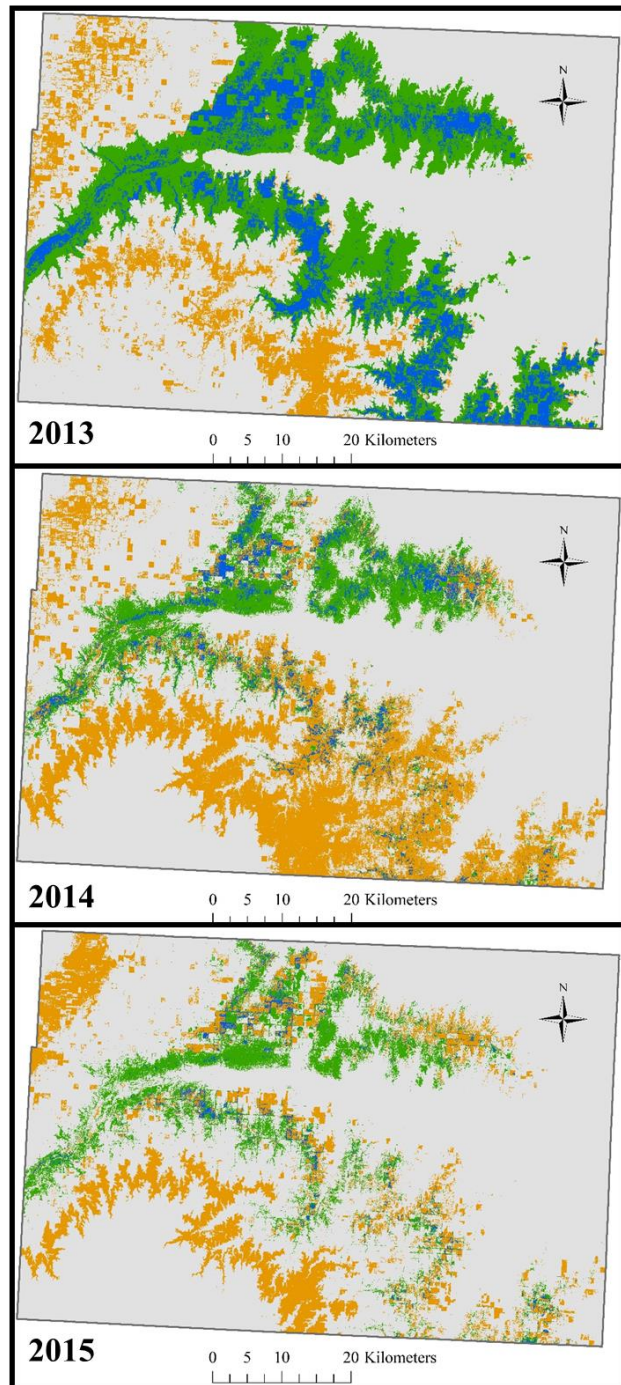


Figure 2.3. Binary suitability output maps for the lesser prairie-chicken (*Tympanuchus pallidicinctus*) and scaled quail (*Callipepla squamata*) as predicted by 30 replicated Maxent models in Beaver County, Oklahoma from April 1, 2013-July 1, 2015. Green indicates areas predicated suitable for scaled quail only, orange for lesser prairie-chicken only, blue for both species, and grey for neither species. Binary maps were created from logistic probability outputs using the maximum sensitivity and specificity threshold rule.

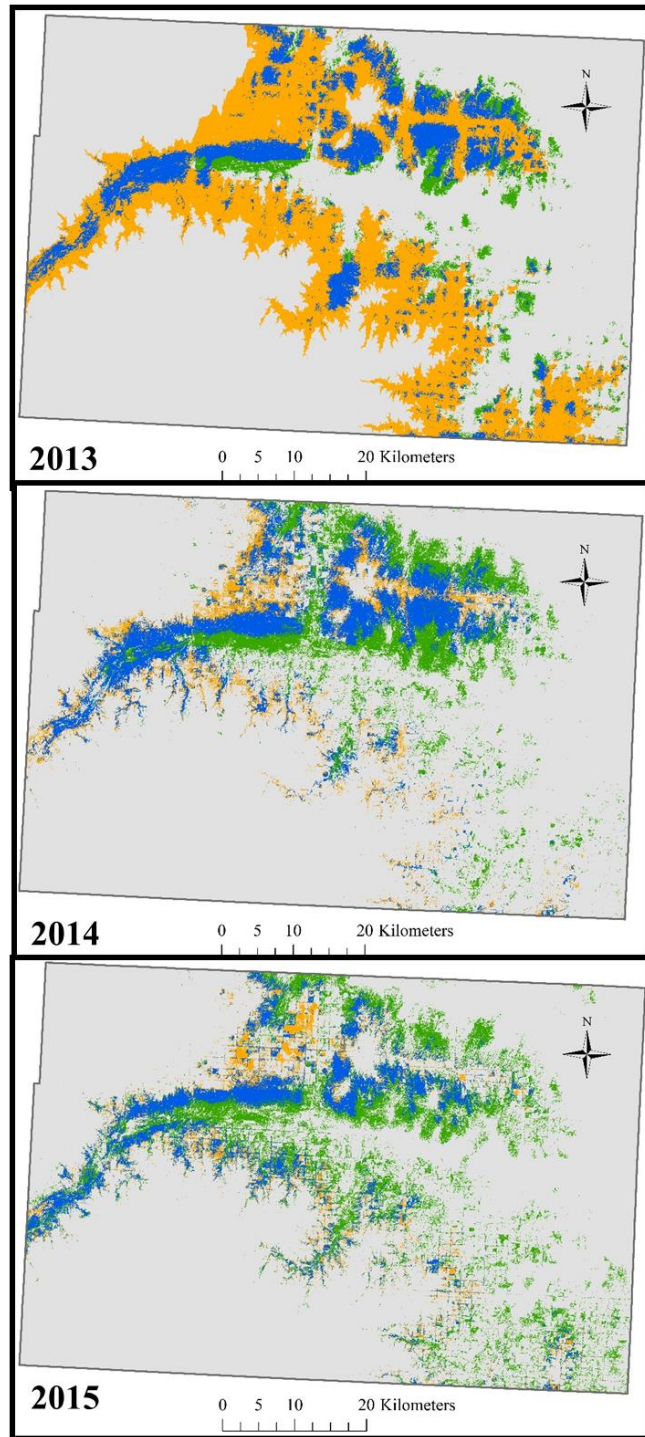


Figure 2.4. Binary suitability output maps for the northern bobwhite (*Colinus virginianus*) and scaled quail (*Callipepla squamata*) as predicted by 30 replicated Maxent models in Beaver County, Oklahoma from April 1, 2013-July 1, 2015. Green indicates areas predicated suitable for northern bobwhite only, orange for scaled quail only, blue for both species, and grey for neither species. Binary maps were created from logistic probability outputs using the maximum sensitivity and specificity threshold rule.

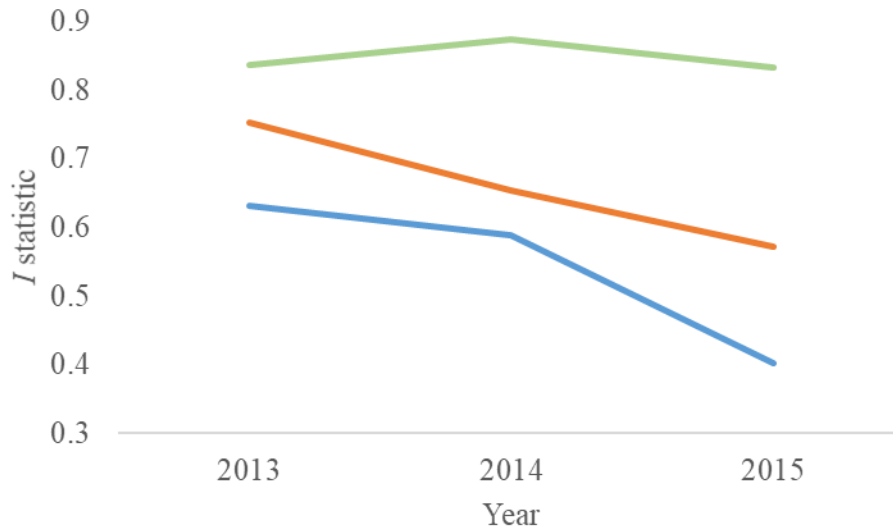


Figure 2.5. Moran's I statistic for measuring niche similarity between lesser prairie-chicken (*Tympanuchus pallidicinctus*), northern bobwhite (*Colinus virginianus*), and scaled quail species distribution models as predicted by 30 replicated Maxent models in Beaver County, Oklahoma from April 1, 2013-July 1, 2015. Green represents the niche similarity of northern bobwhite and scaled quail models, red represents scaled quail and lesser-prairie chicken models, and blue represents northern bobwhite and lesser-prairie chicken models.

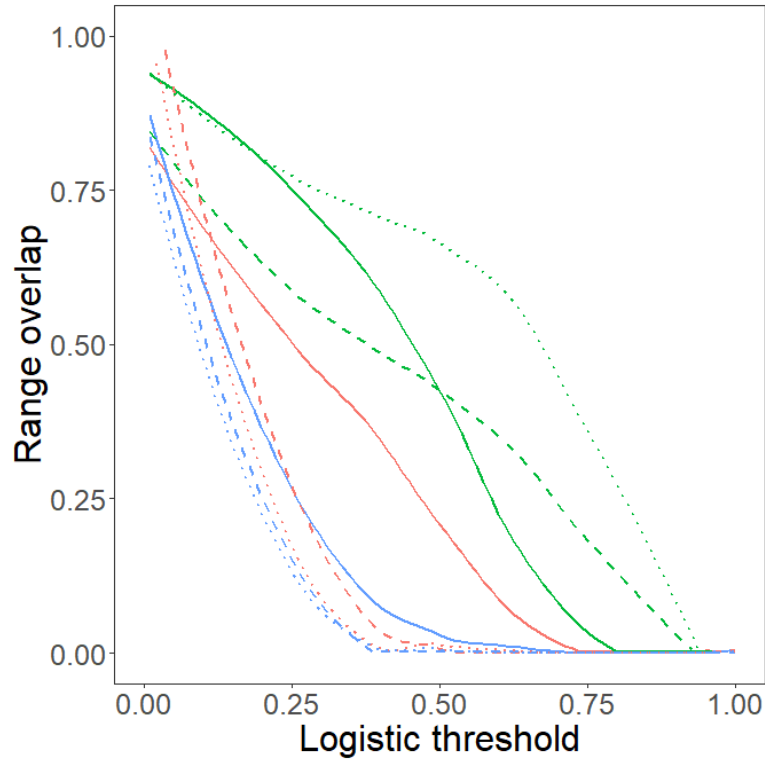


Figure 2.6. Range overlap statistics across varying logistic threshold values for lesser prairie-chicken (*Tympanuchus pallidicinctus*), northern bobwhite (*Colinus virginianus*), and scaled quail species distribution models as predicted by 30 replicated Maxent models in Beaver County, Oklahoma from April 1, 2013-July 1, 2015. Green represents the niche similarity of northern bobwhite and scaled quail models, red represents scaled quail and lesser-prairie chicken models, and blue represents northern bobwhite and lesser-prairie chicken models. Solid lines are models from 2013, dashed lines are from 2014, and dotted lines are from 2015.

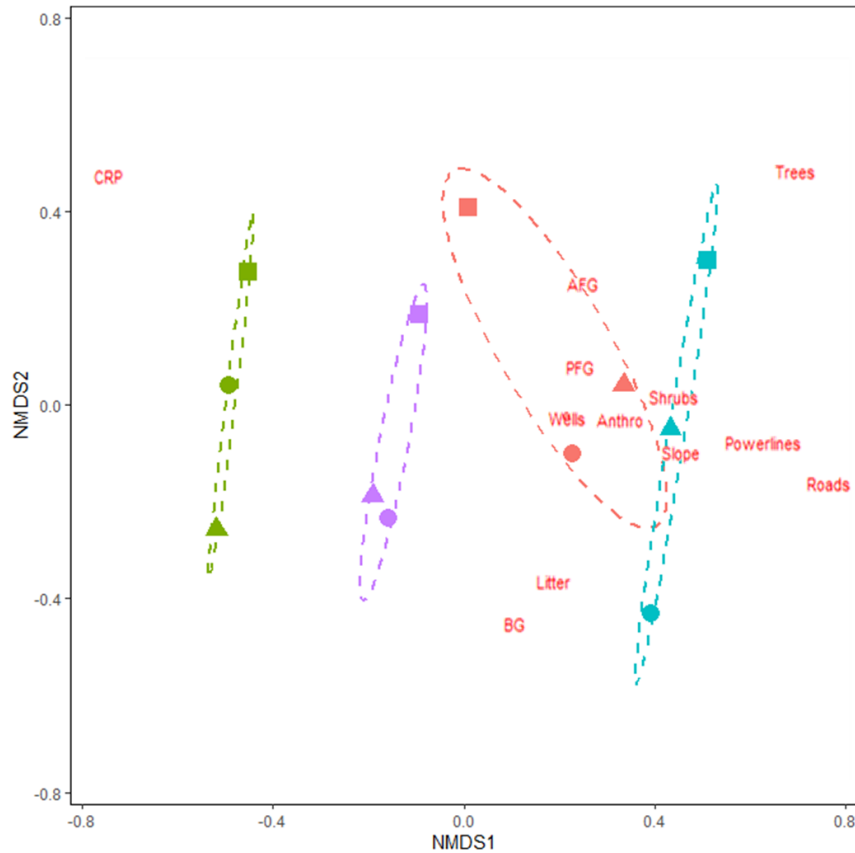


Figure 2.7. Non-metric multidimensional scaling of environmental data^a associated with discrete maps derived from logistic outputs of Maxent models created from northern bobwhite (*Colinus virginianus*) and lesser prairie-chicken (*Tympanuchus pallidicinctus*) data in Beaver County, OK from 2013-2015. Colors represent different map categories (purple: areas predicted unsuitable for both species; green: areas predicted suitable for only lesser prairie-chickens; red: areas predicted suitable for both northern bobwhite and lesser prairie-chickens; cyan: areas predicted suitable for only northern bobwhite). Years are represented by different shapes (circle: 2013; triangle: 2014; square: 2015). Environmental variables are represented in ordinal space by red text.

^aCRP: % cover of the Conservation Reserve Program; BG: % cover of bare ground; Litter: % cover of leaf litter; AFG: % cover of annual forbs and grass; PFG: % cover of perennial forbs and grass; Shrub: % cover of shrubs; Tree: % cover of trees; DEM: elevation (m); Slope: slope of terrain; Anthro: distance (m) to residential areas; Wells: distance (m) to oil/gas wells; Powerlines: distance (m) to powerlines; Roads: distance (m) to roads.

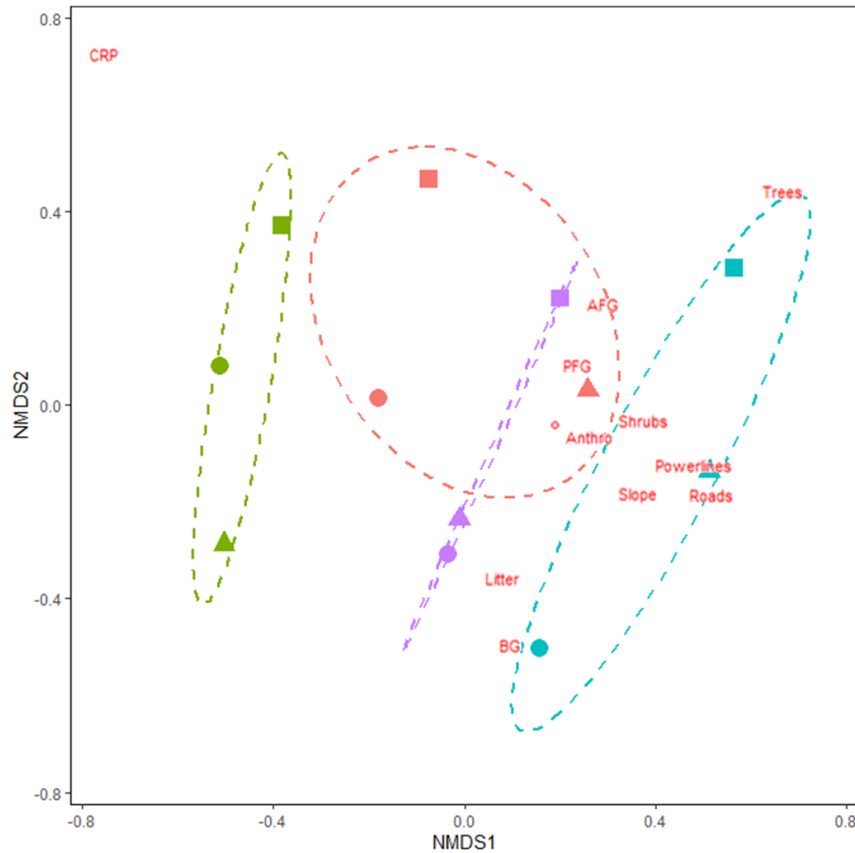


Figure 2.8. Non-metric multidimensional scaling of environmental data^a associated with discrete maps derived from logistic outputs of Maxent models created from scaled quail (*Callipepla squamata*) and lesser prairie-chicken (*Tympanuchus pallidicinctus*) data in Beaver County, OK from 2013-2015. Colors represent different map categories (purple: areas predicted unsuitable for both species; green: areas predicted suitable for only lesser prairie-chickens; red: areas predicted suitable for both northern bobwhite and lesser prairie-chickens; cyan: areas predicted suitable for only scaled quail). Years are represented by different shapes (circle: 2013; triangle: 2014; square: 2015). Environmental variables are represented in ordinal space by red text.

^aCRP: % cover of the Conservation Reserve Program; BG: % cover of bare ground; Litter: % cover of leaf litter; AFG: % cover of annual forbs and grass; PFG: % cover of perennial forbs and grass; Shrubs: % cover of shrubs; Tree: % cover of trees; DEM: elevation (m); Slope: slope of terrain; Anthro: distance (m) to residential areas; Wells: distance (m) to oil/gas wells; Powerlines: distance (m) to powerlines; Roads: distance (m) to roads.

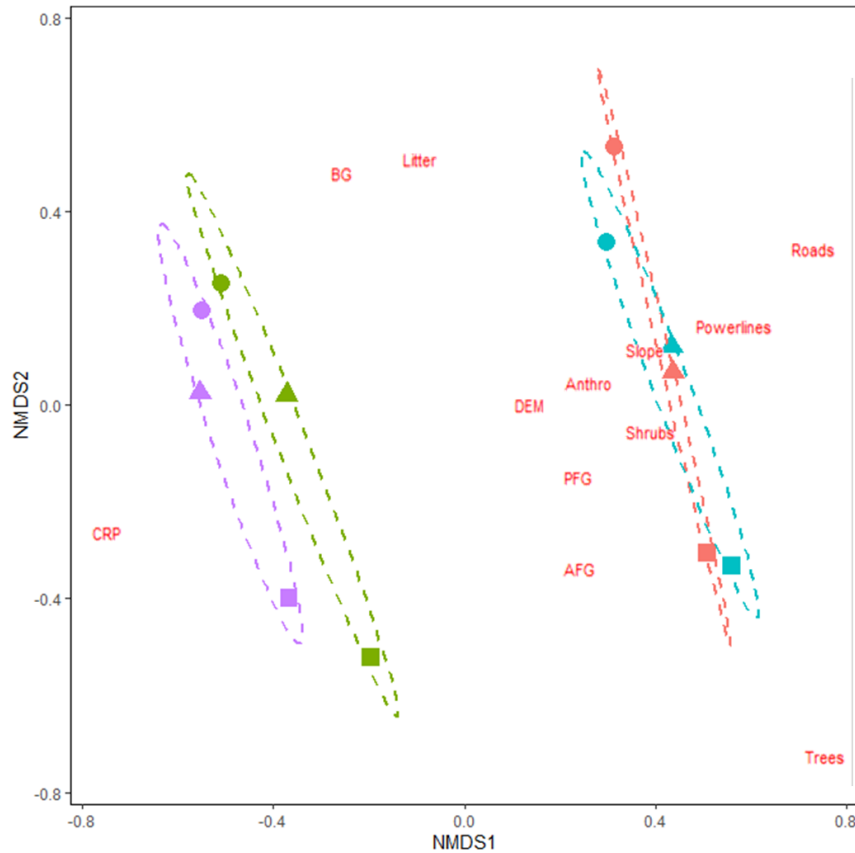


Figure 2.9. Non-metric multidimensional scaling of environmental data^a associated with discrete maps derived from logistic outputs of Maxent models created from scaled quail (*Callipepla squamata*) and northern bobwhite (*Colinus virginianus*) data in Beaver County, OK from 2013-2015. Colors represent different map categories (purple: areas predicted unsuitable for both species; green: areas predicted suitable for only scaled quail; red: areas predicted suitable for both northern bobwhite and scaled quail; cyan: areas predicted suitable for only northern bobwhite). Years are represented by different shapes (circle: 2013; triangle: 2014; square: 2015). Environmental variables are represented in ordinal space by red text.

^aCRP: % cover of the Conservation Reserve Program; BG: % cover of bare ground; Litter: % cover of leaf litter; AFG: % cover of annual forbs and grass; PFG: % cover of perennial forbs and grass; Shrubs: % cover of shrubs; Tree: % cover of trees; DEM: elevation (m); Slope: slope of terrain; Anthro: distance (m) to residential areas; Wells: distance (m) to oil/gas wells; Powerlines: distance (m) to powerlines; Roads: distance (m) to roads.

OBJECTIVE 3 - Determine how mid-contract management of CRP influences movement patterns of LPCs

METHODS

Study site

We conducted our study on a single LPC lek in north-central Beaver County, Oklahoma from April 1, 2014-January 31, 2015. The lek was located on an approximately 122 ha area which was enrolled in CRP in September, 2012. Specifically, the property was enrolled in the Conservation Practice 2 “Establishment of Permanent Native Grasses” with the purpose to reduce soil erosion/sedimentation, improve water quality, and enhance wildlife habitat (https://www.fsa.usda.gov/Internet/FSA_File/appendixb.pdf). As part of a landowner agreement with this Conservation Practice, managed grazing can be used as part of mid-contract management if grazing practices are performed according to the NRCS specifications and may not be grazed more than once every five years. During our study, managed grazing was implemented on July 2, 2014 and was the first time that managed grazing was permitted on this specific CRP pasture. A total of 30 cow/calf pairs were introduced and allowed to graze the pasture for a total of 84 days and all cattle were removed on September 24, 2014.

Lesser Prairie-chicken capture and monitoring

All capture and monitoring protocols were identical to those described in the methods of Objective 2.

Lesser prairie-chicken movement

We extracted a subset of LPC GPS location data associated with a larger project to assess if the introduction of managed grazing on CRP influenced LPC step lengths and habitat selection. To do this, we obtained location data associated with three different periods during our study: pre-grazing (April 1, 2014-July 1, 2014), during grazing (July 2, 2014-September 24, 2014), and post-grazing (September 25, 2014-January 31, 2015). Once locations were assigned to grazing status, we created a step length in ArcGIS 10.2 between subsequent locations by estimating the Euclidean distance between locations. We then used the “isectlinerst” tool in the Geospatial Modeling Environment (GME; Spatial Ecology LLC, Marshfield, Wisconsin) to calculate the proportion of the step length that was within CRP. For each step length, we also determined whether or not the beginning and end of the step was in CRP (i.e., whether or not the individual started and/or ended its movement in CRP).

To determine if patterns predicted from individuals associated with the grazed lek were directly representative of mid-contract management activities rather than seasonal differences in space use, we also extracted GPS locations from the rest of our LPC population within Beaver County (associated with two other leks) that did not encounter mid-contract management during our study period. As such, we considered this our control group, and all locations associated with these individuals were placed into the same grazing statuses and the same CRP information associated with step lengths and location data were extracted for comparisons.

Vegetation monitoring

To monitor the plant community response to managed grazing on the CRP pasture, we conducted vegetation surveys during the pre-, during-, and post-grazing periods. Specifically, vegetation surveys were conducted on June 25, 2014 (pre-grazing), September 24, 2014 (during-grazing), and January 19-21, 2015 (post-grazing). We randomly placed 30 sampling points within the grazed CRP pasture and recorded vegetation characteristics in the same 30 points across all three grazing periods to get repeated measures of the vegetation variables of interest. At each point, we placed a 0.5 m² modified Daubenmire frame (Daubenmire 1959) at the center and in each cardinal direction 4 m away from the point center. Within each frame, we measured the percent cover of plant functional groups (grass, forbs, bare ground, and litter) as well as the percent cover of Old World bluestem (*Bothriochloa ischaemum*), a common non-native invasive grass that was planted in original signups for CRP (McIntyre and Thompson 2003). Additionally, we measured visual obstruction of vegetation by placing a Robel pole (Robel et al. 1970) at the center of each modified Daubenmire frame and estimating where the pole was completely obstructed from view to the nearest decimeter. Finally, we determined the overall vegetation height at the center of each frame using the Robel pole and measuring the maximum height of the vegetation to the nearest centimeter. For our analysis, all vegetation metrics were averaged across the five subsamples at each point to obtain a point average.

Data analysis

Movement analysis

Approximately 34.7% and 14.5% of all step lengths in our treatment and control data sets, respectively, were less than 18 m in length, which was the approximate GPS error associated with the transmitters used during our analysis (Unger 2017). This led to a right-skewed distribution of our response variable that was also zero-inflated. To account for this distribution, we applied a hierarchical two-stage model (Zuur and Ieno 2016) which was comprised of a (1) binomial generalized linear mixed effects model (binomial GLMM) that included the entire data set and a (2) spatial error-truncated log-link Gamma mixed effects model, in which all step lengths shorter than our GPS error were removed from the data set (Taranu et al. 2017). Commonly referred to as a “hurdle” model, this approach is representative of a data set in which to observe an increase in the response variable (step length), a hurdle must first be crossed before an increase is observed (i.e., a movement being greater than the GPS error). This approach helps to address the potential for biased estimates of variance, standard errors, and other parameters associated with over-dispersed data (Moulton et al. 2002) and considers the binomial process (staying still or moving >18 m between locations) and the Gamma process (actually moving between GPS locations) separate because the predictors that determine whether or not an individual moves may be functionally different than predictors that determine the linear relationships of actual LPC movements (Taranu et al. 2017).

Before running models, we determined if our predictive variables (proportion of CRP along a step, movement began in CRP, or movement ended in CRP, grazing status) were correlated using a Chi-squared test. For both datasets, the two variables associated with the start and end of the

movement (movement began in CRP and movement ended in CRP) were highly correlated (treatment data set: $\chi^2 = 1216.1$, d.f.=1, $P < 0.001$; control data set: $\chi^2 = 12680.1$, d.f.=1, $P < 0.001$) and thus we dropped the variable representing whether or not a movement started in CRP. We then started by building binomial GLMMs in which step length was our dependent variable and whether or not a movement ended in CRP and the grazing status were our independent variables. The proportion of CRP within the step length was not included in this stage of our analysis as there was perfect separation and models would not converge. We built models representing univariate, additive, and interactive effects of our independent variables using the package “lme4” in Program R and determined the best performing model by determining the Akaike Information Criterion adjusted for small sample sizes (AIC_c) value for each model and used a ΔAIC_c value of < 2 (Burnham and Anderson 2002) to determine the most parsimonious model for explaining whether or not an individual moved between GPS locations. Once the most parsimonious model was determined, we assessed model fit by calculating the conditional R^2 value of the model using the package “MuMIn” in Program R.

The procedures for building the Gamma GLMMs were identical to our binomial GLMMs except that only the subset of movements > 18 m were included in the analysis and we included the additional independent variable representing the proportion of CRP along the step length. For both the binomial and Gamma GLMMs, we included a random effect which represented each individual in our population and used the “during-grazing” period as the reference period for the categorical variable of grazing status. Furthermore, all analysis procedures were carried out on both our treatment (individuals at the grazed CRP lek) and control (the rest of our sample size) data sets to determine local and population-level trends in step lengths across all three grazing statuses.

Vegetation analysis

To determine if vegetation changed across grazing periods at the grazed lek, we conducted a repeated-measures ANOVA with the corAR1 covariance structure for each functional cover class, vegetation height, and visual obstruction metrics. Each individual point was the unit of replication and was used as a random effect in our models. Significant changes in vegetation metrics were determined at the $\alpha = 0.05$ level.

Results

Movement results

From April 1, 2014-January 31, 2015, a total of 9,433 steps from eight LPC and 22,479 steps from 25 LPC were collected for the treatment and control data sets, respectively. Of these, 6,263 steps from eight LPC, 2,266 steps from four LPC, and 904 steps from four LPC occurred in the treatment data set during the pre-, during-, and post- grazing periods, respectively. In the control data set, a total of 12,810 steps from 25 LPC, 7,433 steps from 13 LPC, and 2,236 steps from 11 LPC occurred during the pre-, during-, and post-grazing periods, respectively.

For both the treatment and control populations, step lengths were lowest in the during-grazing period and greatest in the post-grazing period (Figure 3.1). Other than the during-grazing period,

the control population had larger mean hourly step lengths than the LPC associated with the grazed CRP pasture. The most parsimonious model for the binomial GLMMs included the interactive effects of whether or not the subsequent location was in CRP (LocationInCRP) with the grazing status. This was the top model for both the treatment group (LocationInCRP*Pre-grazing: $\beta = -0.67$, SE = 0.33, $P = 0.04$; LocationInCRP*Post-grazing: $\beta = -13.38$, SE = 3.15, $P < 0.001$; Conditional $R^2 = 0.24$; Table 3.1) and the control group (LocationInCRP*Pre-grazing: $\beta = -0.27$, SE = 0.33, $P = 0.004$; LocationInCRP*Post-grazing: $\beta = 0.23$, SE = 0.13, $P = 0.07$; Conditional $R^2 = 0.22$; Table 3.1). In the treatment group, the probability of moving was influenced by whether or not the subsequent location was in CRP for the pre-grazing (probability to move if subsequent location was in CRP: 0.75; probability to move if subsequent location was not in CRP: 0.87) and post-grazing (probability to move if subsequent location was in CRP: 0.75; probability to move if subsequent location was not in CRP: 0.99) periods (Figure 3.2). Conversely, a subsequent location within CRP was only influential on the probability of moving for the control group during the pre-grazing period (probability to move if subsequent location was in CRP: 0.81; probability to move if subsequent location was not in CRP: 0.87).

The most parsimonious model for the Gamma GLMMs included the interactive effects of whether or not a movement ended in CRP (StepEndCRP) and grazing period, an interactive effect with the proportion of a movement within CRP (ProportionCRP) and grazing period, and the interactive effect of ProportionCRP and StepEndCRP. This again was the top contributing for both the treatment group (StepEndCRP*Pre-grazing: $\beta = 0.40$, SE = 0.17, $P = 0.02$; StepEndCRP*Post-grazing: $\beta = -1.12$, SE = 0.26, $P < 0.001$; ProportionCRP*Pre-grazing: $\beta = -0.46$, SE = 0.22, $P = 0.04$; ProportionCRP*Post-grazing: $\beta = 2.44$, SE = 0.33, $P < 0.001$; StepEndCRP*ProportionCRP: $\beta = -3.04$, SE = 0.19, $P < 0.001$; Conditional $R^2 = 0.32$; Table 3.2) and the control group (StepEndCRP*Pre-grazing: $\beta = 0.47$, SE = 0.09, $P < 0.001$; StepEndCRP*Post-grazing: $\beta = 0.27$, SE = 0.14, $P = 0.6$; ProportionCRP*Pre-grazing: $\beta = -0.80$, SE = 0.10, $P < 0.001$; ProportionCRP*Post-grazing: $\beta = -0.96$, SE = 0.17, $P < 0.001$; StepEndCRP*ProportionCRP: $\beta = -4.70$, SE = 0.10, $P < 0.001$; Conditional $R^2 = 0.30$; Table 3.2). Both models predicted greater mean hourly step lengths for the post-grazing period as the percentage of that step length increased in CRP coverage (Figure 3.3) although disparate relationships during the pre- and during-grazing periods, in which movements for the treatment group were shorter when a greater amount of the step length was within CRP (Figure 3.3). Similarly, post-grazing movements were greater for both treatment and control groups when the movement did not end in CRP (Figure 3.4). However, step lengths did not differ across grazing periods when a movement ended in CRP for the treatment group where-as there were differences for the control group (Figure 3.4). Finally, we found similar relationships across treatment and control groups with regards to the interaction between the proportion of the step length in CRP and whether or not the movement ended in CRP (Figure 3.5). The relationships across both groups indicated higher step lengths when moving between non-CRP and CRP, and smaller movements when staying within the same cover class category, suggesting large movements moving to and from CRP patches.

Table 3.1. Akaike's Information Criterion adjusted for small sample size (AIC_c) model selection results for binomial generalized linear mixed effects models assessing the influence of the Conservation Reserve Program (CRP) on the probability of a lesser prairie-chicken (*Tympanuchus pallidicinctus*) movement within Beaver County, OK from April 1, 2014-January 31, 2015.

Group ^a	Model ^b	AIC_c	ΔAIC_c	K^c	Weight ^d	Log Likelihood
Treatment	LocationInCR*GrazingStatus	9396.07	0	7	1	-4691.03
	LocationInCRP + GrazingStatus	9408.13	12.06	5	0	-4699.06
	GrazingStatus	9454.45	58.38	4	0	-4723.22
	LocationInCRP	9615.99	219.92	3	0	-4804.99
	Null	9651.74	255.67	2	0	-4823.87
Control	LocationInCRP*GrazingStatus	20205.1	0	7	1	-10095.33
	LocationInCRP + GrazingStatus	20222.3	17.25	5	0	-10106.16
	GrazingStatus	20270.5	65.41	4	0	-10131.24
	LocationInCRP	20352	146.96	3	0	-10173.01
	Null	20376.7	171.66	2	0	-10186.36

^aTreatment represents individuals associated with a lek in which mid-contract managed grazing occurred from July 2, 2014-September 24, 2014. Control represents all other individuals not associated with this lek and grazing event.

^bLocationInCRP indicates whether or not a subsequent hourly location was located in CRP. GrazingStatus represents pre-grazing (April 1, 2014-July 1, 2014), during-grazing (July 2, 2014-September 24, 2014), and post-grazing (September 25, 2014-January 31, 2015) periods.

^cNumber of parameters

^dModel weight based on AIC_c values

Table 3.2. Akaike's Information Criterion adjusted for small sample size (AIC_c) model selection results for Gamma distributed generalized linear mixed effects models assessing the influence of the Conservation Reserve Program (CRP) on lesser prairie-chicken (*Tympanuchus pallidicinctus*) mean hourly step lengths (m) within Beaver County, OK from April 1, 2014-January 31, 2015.

Group ^a	Model ^b	AIC _c	ΔAIC _c	K ^c	Weight ^d	Log Likelihood
Treatment	StepEndCRP*GrazingStatus + ProportionCRP*GrazingStatus + ProportionCRP*StepEndCRP	87099.5	0.0	12.0	1.0	-43537.7
	ProportionCRP*StepEndCRP + GrazingStatus	87176.1	76.7	8.0	0.0	-43580.0
	StepEndCRP*GrazingStatus + ProportionCRP*GrazingStatus	87358.9	259.4	11.0	0.0	-43668.4
	StepEndCRP + ProportionCRP + GrazingStatus	87436.6	337.2	7.0	0.0	-43711.3
	StepEndCRP + ProportionCRP	57477.0	377.6	5.0	0.0	-43733.5
	StepEndCRP	57479.6	380.1	4.0	0.0	-43735.8
	ProportionCRP	87617.1	517.6	4.0	0.0	-43804.5
	Null	87624.3	524.8	3.0	0.0	-43809.1
Control	StepEndCRP*GrazingStatus + ProportionCRP*GrazingStatus + ProportionCRP*StepEndCRP	214507.0	0.0	12.0	1.0	-107241.5
	ProportionCRP*StepEndCRP + GrazingStatus	214619.2	112.2	8.0	0.0	-107301.6
	StepEndCRP*GrazingStatus + ProportionCRP*GrazingStatus	217757.4	3250.4	11.0	0.0	-108867.7
	StepEndCRP + ProportionCRP + GrazingStatus	217878.1	3371.1	7.0	0.0	-108932.0
	StepEndCRP + ProportionCRP	218391.4	3884.4	5.0	0.0	-109190.7
	ProportionCRP	218436.1	3929.1	4.0	0.0	-109214.1
	StepEndCRP	218682.2	4175.2	4.0	0.0	-109337.1
	Null	219100.8	4593.8	3.0	0.0	-109547.4

^aTreatment represents individuals associated with a lek in which mid-contract managed grazing occurred from July 2, 2014-September 24, 2014. Control represents all other individuals not associated with this lek and grazing event.

^bLocationInCRP indicates whether or not a subsequent hourly location was located in CRP. GrazingStatus represents pre-grazing (April 1, 2014-July 1, 2014), during-grazing (July 2, 2014-September 24, 2014), and post-grazing (September 25, 2014-January 31, 2015) periods.

^cNumber of parameters

^dModel weight based on AIC_c values

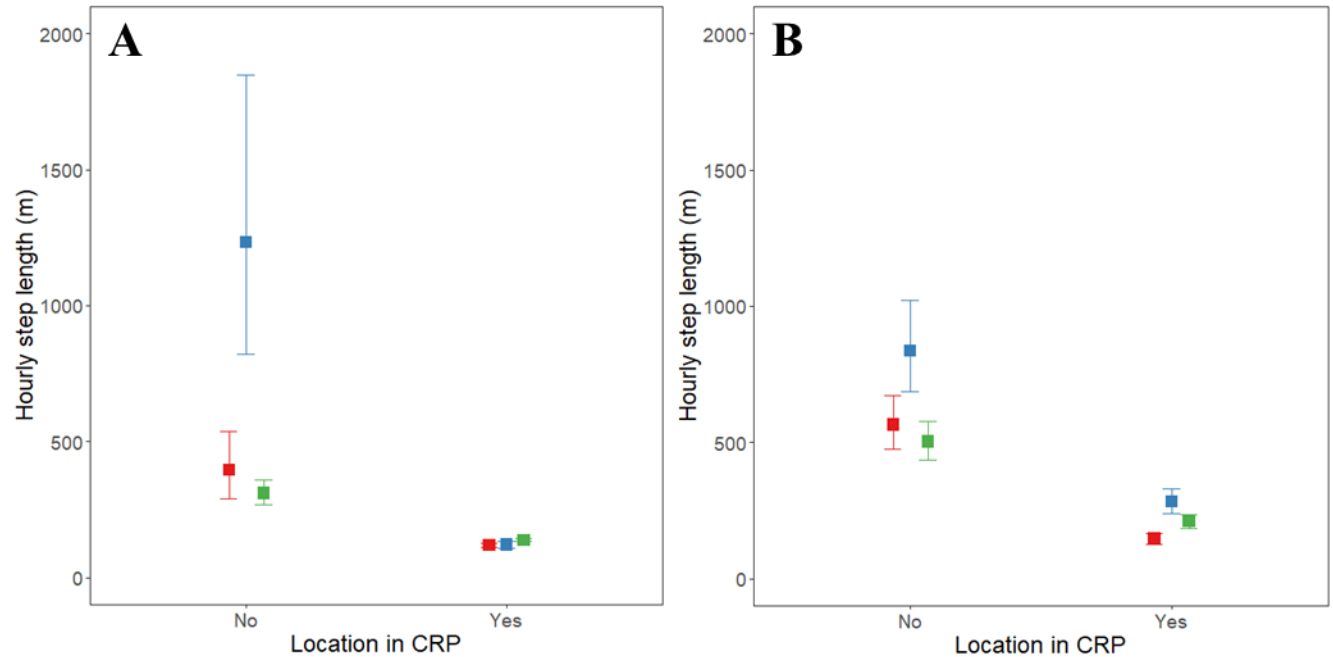


Figure 3.1. Mean hourly step lengths of lesser prairie-chickens (*Tympanuchus pallidicinctus*) in Beaver County, OK from April 1, 2014-January 31, 2015. Panels represent (A) individuals that were associated with a lek that underwent mid-contract managed grazing within the Conservation Reserve Program (CRP) and (B) all other marked individuals not associated with the lek undergoing mid-contract grazing. Grazing statuses are represented in time by pre-grazing (April 1, 2014-July 1, 2014), during-grazing (July 2, 2014-September 24, 2014), and post-grazing (September 25, 2014-January 31, 2015).

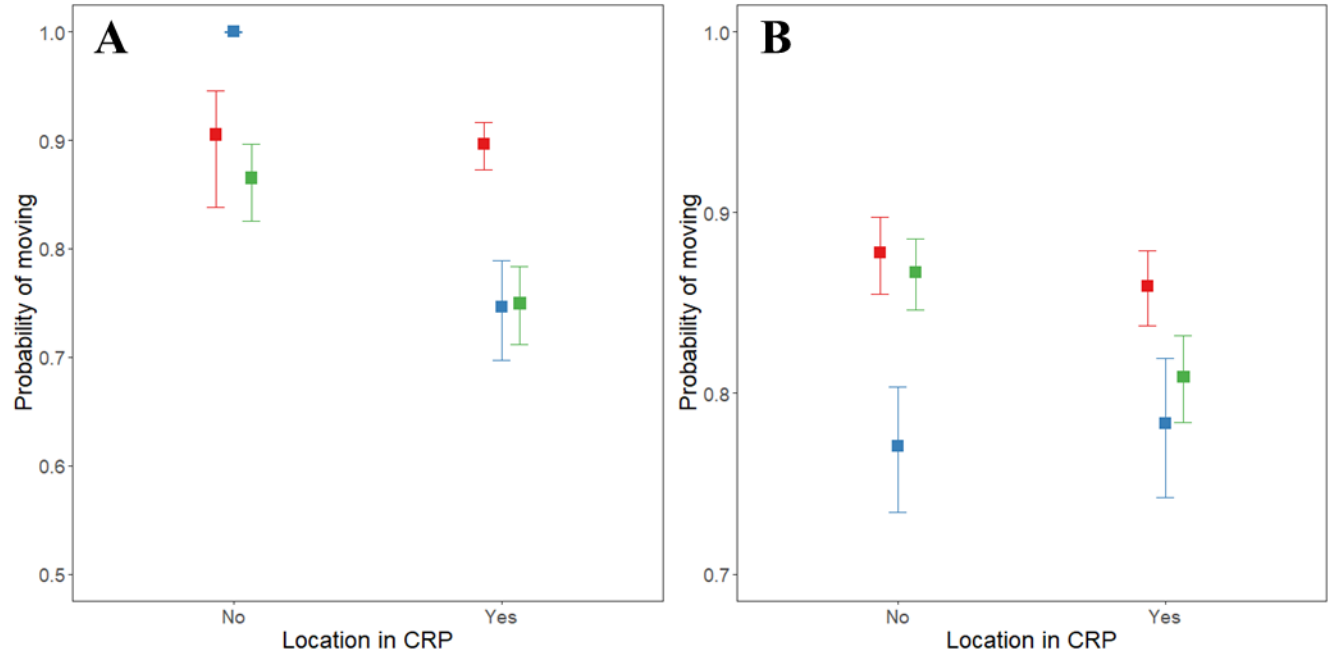


Figure 3.2. Probability of a lesser prairie-chicken (*Tympanuchus pallidicinctus*) moving across subsequent hourly locations in relation to whether or not a subsequent location was within the Conservation Reserve Program (CRP) in Beaver County, OK. Panels represent (A) individuals that were associated with a lek that underwent mid-contract managed grazing within the CRP and (B) all other marked individuals not associated with the lek undergoing mid-contract grazing. Grazing statuses are represented in time by pre-grazing (April 1, 2014-July 1, 2014 [green]), during-grazing (July 2, 2014-September 24, 2014 [red]), and post-grazing (September 25, 2014-January 31, 2015 [blue]).

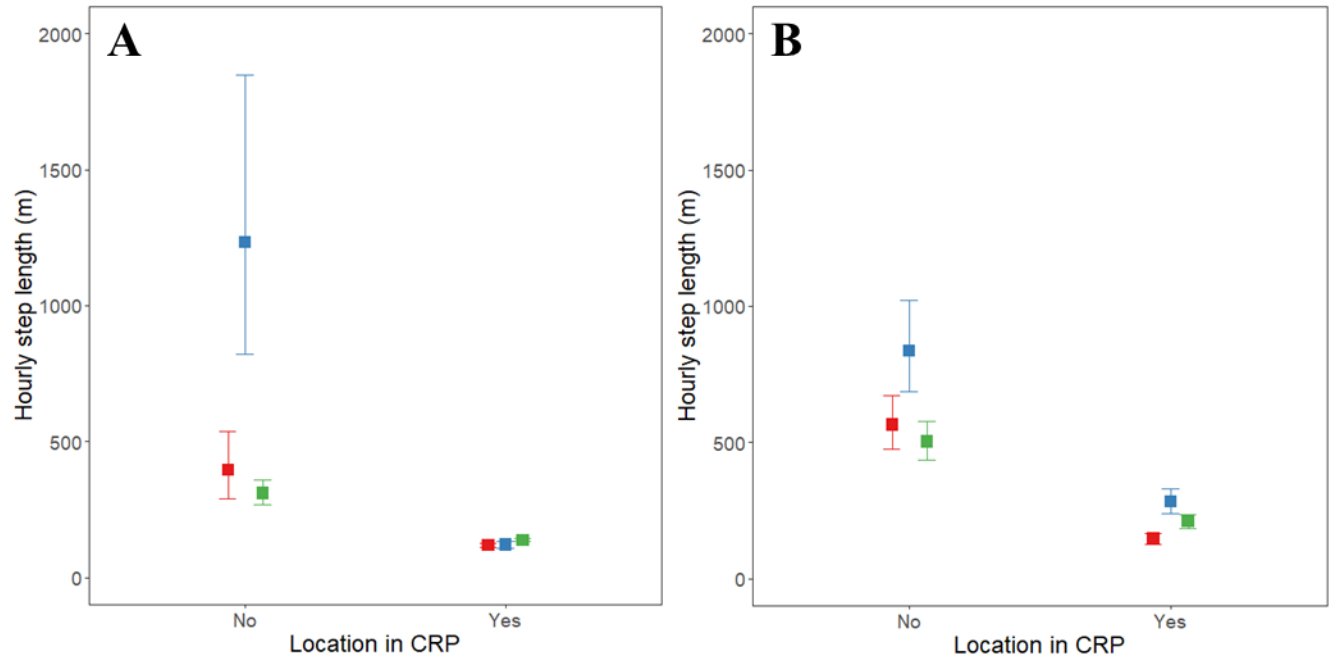


Figure 3.3. Mean hourly step length (m) of lesser prairie-chicken (*Tympanuchus pallidicinctus*) movements in relation to whether or not the movement ended within the Conservation Reserve Program (CRP) in Beaver County, OK. Panels represent (A) individuals that were associated with a lek that underwent mid-contract managed grazing within the CRP and (B) all other marked individuals not associated with the lek undergoing mid-contract grazing. Grazing statuses are represented in time by pre-grazing (April 1, 2014-July 1, 2014 [green]), during-grazing (July 2, 2014-September 24, 2014 [red]), and post-grazing (September 25, 2014-January 31, 2015 [blue]).

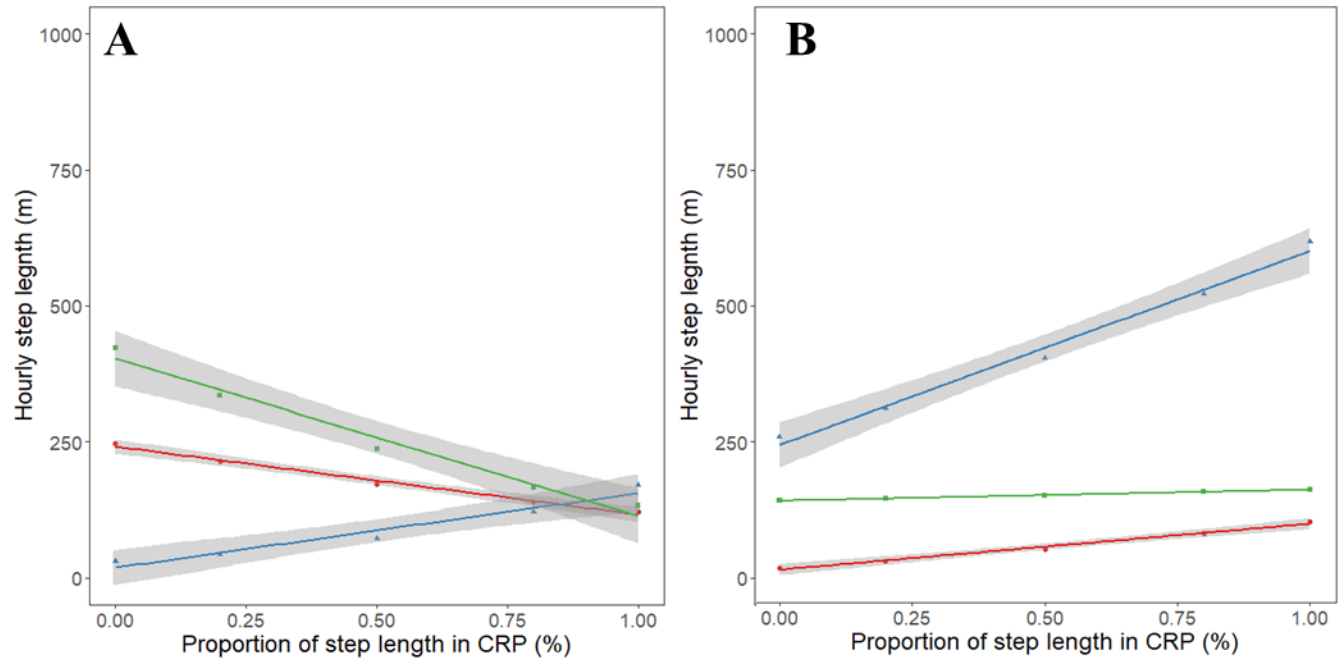


Figure 3.4. Mean hourly step length (m) of lesser prairie-chicken (*Tympanuchus pallidicinctus*) movements in relation to the proportion of the step length located within the Conservation Reserve Program (CRP) in Beaver County, OK. Panels represent (A) individuals that were associated with a lek that underwent mid-contract managed grazing within the CRP and (B) all other marked individuals not associated with the lek undergoing mid-contract grazing. Grazing statuses are represented in time by pre-grazing (April 1, 2014-July 1, 2014 [green]), during-grazing (July 2, 2014-September 24, 2014 [red]), and post-grazing (September 25, 2014-January 31, 2015 [blue]). Grey areas represent 95% confidence intervals.

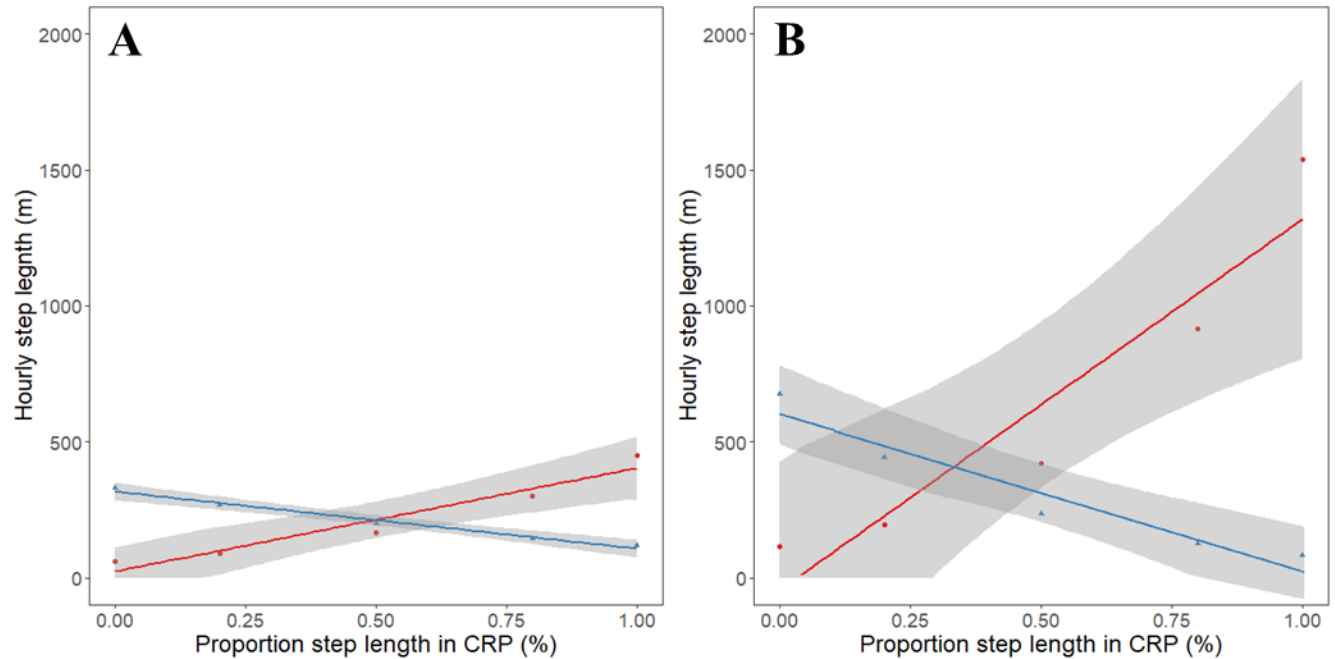


Figure 3.5. Mean hourly step length (m) of lesser prairie-chicken (*Tympanuchus pallidicinctus*) movements in relation to the proportion of the step length located within the Conservation Reserve Program (CRP) in Beaver County, OK. Panels represent (A) individuals that were associated with a lek that underwent mid-contract managed grazing within the CRP and (B) all other marked individuals not associated with the lek undergoing mid-contract grazing. The red lines indicate when the end of a movement was not located in CRP and the blue line represents when the end of a movement was in CRP. Grey areas represent 95% confidence intervals.

Vegetation response

Based on our repeated-measures sampling, the only difference in vegetation metrics across the pre-, during-, and post-grazing period was associated with vegetation height (Table 3.3). Vegetation height was statistically lower during the post-grazing period when compared to the pre- and during-grazing periods ($P < 0.001$).

Table 3.3. Average values of vegetation metrics measured on a Conservation Reserve Program (CRP) pasture across 30 plots that experienced mid-contract managed grazing in Beaver County, OK. Grazing statuses are represented in time by pre-grazing (April 1, 2014-July 1, 2014), during-grazing (July 2, 2014-September 24, 2014), and post-grazing (September 25, 2014-January 31, 2015). Statistical differences were determined using a repeated-measures ANOVA with a corAR1 covariance structure.

Vegetation metric	Grazing status	\bar{x}	SE ^a	df ^b	F	P
% bare ground	Pre	13.10	1.71			
	During	11.71	1.12	59	1.39	0.24
	Post	15.33	1.32			
% forb	Pre	6.17	1.39			
	During	11.37	1.40	59	0.36	0.55
	Post	7.17	1.33			
% grass	Pre	63.73	3.66			
	During	65.90	2.50	59	1.37	0.25
	Post	60.00	2.60			
% leaf litter	Pre	15.70	3.14			
	During	9.97	0.88	59	0.04	0.83
	Post	16.30	1.33			
% Old World Bluestem	Pre	1.30	1.01			
	During	1.13	0.63	59	0.02	0.90
	Post	1.20	1.17			
Vegetation height (cm)	Pre	52.05	2.71			
	During	52.33	2.93	59	229.77	<0.001
	Post	19.56	1.07			
Visual obstruction (dm)	Pre	1.82	0.13			
	During	1.46	0.09	59	0.004	0.95
	Post	1.83	0.10			

^aStandard error

^bDegrees of freedom

OBJECTIVE 4- Determine how CRP influences nighttime roost site selection and movement patterns to roost sites

METHODS

For this objective, our study site and LPC capturing and monitoring protocols were all identical to those described in Objective 2 and the data associated with this study was collected from April 2013-May 2016. Once LPC GPS location data were obtained from our larger data set, we extracted locations that occurred after sunset and before sunrise of the next day to represent nocturnal roost locations. We then calculated the number of hours between the individual's previous location and the roost location and removed locations that had > six hours between the previous location and the roost location (approximately 8.8% of the total data set). We did this to help prevent any spurious relationships in which too much time had occurred between the roost location and the previous location. We note that the minimum time between a roosting location and the previous location was four hours.

Once locations were obtained, we created step lengths in ArcGIS 10.2 between the roost location and the previous location by estimating the Euclidean distance between locations. We then calculated the proportion of the step length that was within CRP. For each step length, we also determined whether or not the beginning and end of the step was in CRP (i.e., whether or not the individual started and/or ended its movement in CRP), similar to Objective 3. Finally, we visually assessed average hourly movement (m) patterns across all individuals annually and plotted these movement patterns to determine specific seasons related to changes in average movement patterns (Figure 4.1). Based on these patterns, we assigned roost locations into four specific seasons: Breeding (March 27-May 31), Summer (June 1-August 31), Fall Transition (September 1-November 30), and Winter (December 1-February 28).

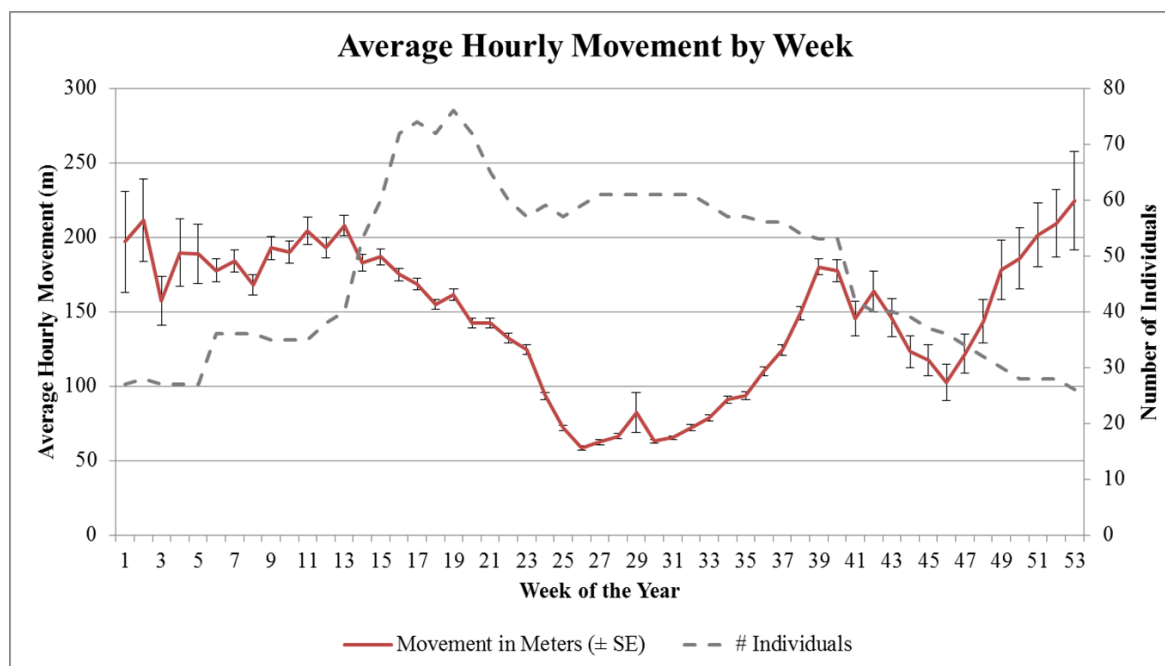


Figure 4.1. Average hourly movement (m) distances of lesser prairie-chickens (*Tympanuchus pallidicinctus*) from April 2013-May 2016 in Beaver County, OK. Number of individuals are represented by the dashed line and standard errors are presented by vertical lines for movement distances.

Environmental data

Landcover data

We used a vegetation classification dataset created through the Oklahoma ecological systems mapping project which was created using an object-based classification approach and verified via ground-truthing. Landsat Thematic Mapper satellite data were used alongside the ground-truthed sample locations to help categorize landcover types through a decision tree classification approach, resulting in a 30 m spatial grain for landcover data. Then, an image object-based classification approach was used to resample the 30 m landcover data to a 10 m grain through the use of a National Agriculture Imagery Program image mosaic. A more detailed explanation of the process involved with creating this landcover data set can be found in Diamond and Elliot (2015).

After initial assessment of the Oklahoma ecological systems mapping data, we chose to simplify the vegetation categories into six general cover classes: croplands, mixed grass prairie, planted grass (typically Old World bluestem), barren land, ruderal shrub, and shortgrass prairie. Additionally, we incorporated a spatially explicit CRP layer into the landcover raster which included all CRP land enrolled as of January of 2016. This layer was obtained through the Oklahoma Farm Service Agency (FSA). We allowed the CRP layer to take precedence over landcover data associated with the Oklahoma ecological systems mapping project such that CRP became its own cover class, resulting in a total of seven landcover classes. Finally, we converted our landcover data into distance based rasters using the Euclidian Distance tool in ArcGIS 10.2 to create distance (m) to each vegetation type.

Anthropogenic data

We created distance-based rasters to multiple anthropogenic features. The anthropogenic rasters included in our analysis were distance to: active oil/gas wells, power lines, residential areas, and roads. We obtained the location of oil/gas wells, and power lines, from the Western Associated of Fish and Wildlife Agencies. We obtained a roads layer through the USDA GeoSpatial Data Gateway to access the TIGER shapefile depicting primary and secondary roads throughout the county. We obtained residential area data by hand mapping these locations in ArcGIS 10.2 using 2013 USDA NAIP imagery within Beavary county. Once all spatially explicit anthropogenic feature data were obtained, we created a Euclidean distance-based raster for each feature type at a 30 m resolution to match the spatial grain of the RAP rasters.

Finally, to assess potential novel anthropogenic influences distinct to nighttime disturbances, we incorporated a visible infrared imaging radiometer suite (VIIRS) data set which images nighttime light pollution globally at a 742 m nominal spatial resoltuion and is provided by the National Oceanic and Atmospheric Administration (NOAA; <https://sos.noaa.gov/datasets/nighttime-lights/>).

Other variables

The only other environmental variable we included in our analysis was the distance to a LPC's lek of capture (m). This resulted in a total of 14 environmental variables and all environmental variables (except the nighttime lights layer) were resampled at a grain of 36 m to represent the ~18 m error associated with our GPS transmitters.

Data analysis

Roost site habitat selection

We used the proportional hazard regression (PHREG) procedure in SAS (SAS 2000) to estimate parameters associated with roost site selection and to produce AIC_c values to determine the most parsimonious model with models having a $\Delta AIC_c < 2$ being considered plausible models. This procedure allowed us to use discrete choice models, which allow for availability of resources to change over time (Ben-Akiva and Lerman 1985, Cooper and Millspaugh 1999). To determine available resources relative to LPC, we created a circle buffer around each individual roost location with a radius equal to 1,010 m, which represented double the largest average movement made to or from a roost site across seasons. Once buffers were created, we created five random points within each location buffer and considered these points to be available yet not used for roost locations. The five random locations and the one used location represented a “choice set”, which is considered an individual sample and is equal to the number of roost locations within our data set (Cooper and Millspaugh 1999). Within all models, we included an error term accounting for individual birds.

All choice sets were match with the 14 spatially explicit environmental variables described previously. To meet the assumption of the discrete choice model, we conducted a correlation analysis in SAS (SAS 2000) and removed any variables with a Pearson’s correlation coefficient of $|r| \geq 0.70$. No variables were highly correlated so we retained the original set of environmental variables.

We built an initial model suite assessing the interaction between season and all environmental variables within our data set. Thus, our initial model suite contain 14 interactive models with an additional null model (15 total models). We simplified the complexity of our models in this initial suite because including a large number of variable in a discrete choice model could cause a bias and unstable parameter estimation (McCracken et al. 1998). We then built a post-hoc model suite assessing semi-global models associated with comparing roost site selection with vegetation-only variables versus anthropogenic-only variables. This was to determine if roost site selection was driven more by existing vegetation on the landscape or by anthropogenic disturbances. Finally, we used a likelihood ratio test to assess the overall model fit by comparing the log-likelihoods between the null model and our most parsimonious model (McCullagh and Nelder 1989).

Movement to roost analysis

Similar to Objective 3, we used a Gamma distributed generalized linear mixed effects model (GLMM) to determine if CRP was influencing the step length between roost sites and movements to the roost sites (previous location before a roosting location). Because we were ultimately interested in movement patterns, we eliminated any data points in which an individual did not move to the roost site prior to sunset (~38.4% of locations). Two of our explanatory variables (whether or not the movement to the roost site started in CRP and whether or not the movement to the roost site ended in CRP) were highly correlated ($\chi^2 = 8,806$, $df = 1$, $P < 0.001$), thus we retained the variable indicating whether or not the movement to the roost site ended in CRP, as the ultimately represented whether or not a roost site was located in CRP, coinciding with our resource selection analysis.

We built Gamma distributed GLMMs in which step length to the roost site was our dependent variable and whether or not a movement ended in CRP and the proportion of CRP within the step length were our independent variables. We built models representing univariate, additive, and interactive effects of our independent variables using the package “lme4” in Program R and determined the best performing model by determining the Akaike Information Criterion adjusted for small sample sizes (AIC_c) value for each model and used a ΔAIC_c value of <2 (Burnham and Anderson 2002) to determine the most parsimonious model for explaining whether or not an individual moved between GPS locations.

RESULTS

From April 2013-May 2016, we captured a total of 106 LPC (72 males, 34 females) resulting in a total of 219,322 GPS locations. Of these, we obtained a total of 36,201 nocturnal locations from 91 LPC. We also obtained a total of 15,076 movements to the roost locations from 91 LPC. Nocturnal roost sample sizes were greatest during the breeding season and lowest during the winter season (Figure 4.2). On average, movements off of roost sites were further when compared to movements to the roost site or diurnal movement rates (Figure 4.3). Similarly, besides the winter season, movements to the roost site were greater than diurnal movement patterns when compared within seasons.

Discrete choice analysis

Based on model selection results for our discrete choice models, the best model explaining resource selection for LPC roost sites included an interaction between season and shortgrass prairie (Table 4.1). This was the most parsimonious model and no other models were considered plausible. Based on this model, avoidance for roost sites in shortgrass prairie vegetation was strongest during the summer season ($\beta = 0.0019$, 95% CI = 0.0015-0.0024, $P < 0.001$) and during the winter season ($\beta = 0.0045$, CI = -0.0042-0.0048, $P < 0.001$). We note that since these are distance-based variables, a positive β indicates an avoidance of this variable. When assessing global models comparing a model with only vegetation variables to a model with only anthropogenic variables, model selection results indicated that vegetation was more important to roost site selection than the influence of anthropogenic features (Table 4.2). Of the vegetation variables influencing roost site selection, LPC located roost sites closer to CRP, their lek of capture, croplands, and mixed grass prairie than would be expected at random (Table 4.3). Of these, CRP was the most influential variable influencing roost site selection. Conversely, individuals located roost sites further from barren lands, shrubs, and shortgrass prairie than would be expected at random (Table 4.3).

Movement to roost analysis

Two models were considered plausible models in explaining LPC movement to roost sites and were contained with a $\Delta AIC_c < 2$ (Table 4.4). Within these two models, the variables indicating the proportion of CRP along the step length to the roost site (ProportionCRP) and whether or not the roost site was in CRP (RoostInCRP) were both included in the top two models. The sex of an individual was also included in the second best support model, but was not considered significant as its β estimate had a confidence interval overlapping 0 ($\beta = 0.21$, SE = 0.18, $P = 0.23$).

Parameter estimates for the two CRP variables indicated that as movements to the roost site contained more CRP along the step length, movements decreased ($\beta = -1.01$, $SE = 0.06$, $P < 0.001$; Figure 4.4) whereas movements to the roost were greater when a roost site was in CRP as opposed to outside CRP ($\beta = 0.57$, $SE = 0.05$, $P < 0.001$; Figure 4.5). This suggests that individuals located outside of CRP before sunset are moving longer distances to get to roost sites in CRP, but if they were already located in CRP before moving to the roost site (i.e., 100% of their movement to the roost was in CRP), they moved significantly less to get to their roost within CRP.

Table 4.1. Akaike's Information Criterion adjusted for small sample size (AIC_c) model selection results for discrete choice models assessing the influence of interactions between season and vegetation/anthropogenic variables on the roost site selection lesser prairie-chickens (*Tympanuchus pallidicinctus*) within Beaver County, OK from April 2014-May 2016.

Model	AIC _c	ΔAIC _c	K ^a	Weight ^b
Season*Shortgrass	53845.7	0	4	1
Season*LekDistance	55156.7	1311	4	0
Season*Powerline	56511.1	2665.4	4	0
Season*CRP	56767.3	2921.61	4	0
Season*Roads	56956.6	3110.91	4	0
Season*Shrub	58077.3	4231.6	4	0
Season*PlantedGrass	59320.9	5475.2	4	0
Season*MixedGrass	59520.5	5674.81	4	0
Season*NightLights	59591.7	5745.99	4	0
Season*Wells	59607.9	5762.19	4	0
Season*Crops	59327.3	5781.54	4	0
Season*Residential	59632.3	5786.6	4	0
Season*Barren	59635.6	5789.87	4	0
Null	59683.5	5837.78	1	0

^aNumber of parameters

^bModel weight based on AIC_c

Table 4.2. Akaike's Information Criterion adjusted for small sample size (AIC_c) model selection results for discrete choice models assessing the influence of a vegetation global model (only containing vegetation-related variables) and an anthropogenic global model (only containing anthropogenic-related variables) on the roost site selection lesser prairie-chickens (*Tympanuchus pallidicinctus*) within Beaver County, OK from April 2014-May 2016.

Model	AIC_c	ΔAIC_c	K^a	Weights ^b
Vegetation Only	49396.9	0	8	1
Anthropogenic Only	51524.3	2127.33	7	0
Null	59683.5	10286.6	1	0

^aNumber of parameters

^bModel weight based on AIC_c

Table 4.3. Parameter estimates, 95% confidence intervals, and associated significance values for variables within the vegetation global model as calculated from a discrete choice model assessing the influence of a vegetation global model on the roost site selection lesser prairie-chickens (*Tympanuchus pallidicinctus*) within Beaver County, OK from April 2014-May 2016.

Model	Variable	β	Lower 95% CI	Upper 95% CI	<i>P</i>
Vegetation Only	CRP	-0.0023	-0.0025	-0.0022	<0.0001
	Lek Distance	-0.0012	-0.0012	-0.0011	<0.0001
	Cropland	-0.0007	-0.0008	-0.0006	<0.0001
	Mixed grass	-0.0001	-0.0002	-0.0001	0.0159
	Planted grass	0	-0.0001	0.0002	0.5344
	Barren	0.0003	0.0003	0.0004	<0.0001
	Ruderal shrub	0.0005	0.0004	0.0005	<0.0001
	Shortgrass	0.0045	0.0043	0.0046	<0.0001

Table 4.4. Akaike's Information Criterion adjusted for small sample size (AIC_c) model selection results for Gamma distributed GLMMs assessing the influence of CRP on the movement lengths of movements to roost sites for lesser prairie-chickens (*Tympanuchus pallidicinctus*) within Beaver County, OK from April 2014-May 2016.

Model ^a	AIC _c	ΔAIC _c	K ^b	Weight ^c	Log Likelihood
ProportionCRP + RoostInCRP	108522.0	0.0	5.0	0.6	-54256.0
Sex + ProportionCRP + RoostInCRP	108522.6	0.6	6.0	0.4	-54255.3
ProportionCRP	108674.7	152.6	4.0	0.0	-5433.3
Sex + ProportionCRP	108675.3	153.2	5.0	0.0	-54332.6
Null	108834.9	312.9	3.0	0.0	-54414.5
Sex	108835.7	313.7	4.0	0.0	-54413.8
RoostInCRP	108835.9	313.8	4.0	0.0	-54413.9
Sex + RoostInCRP	108836.7	314.6	5.0	0.0	-54413.3

^aVariables represent: ProportionCRP: the proportion of CRP along the step length of the movement to a roost site; RoostInCRP: whether or not the end of the movement to the roost, and additionally, the roost site, are in CRP; Sex: sex of the individual

^bNumber of parameters

^c Model weight based on AIC_c

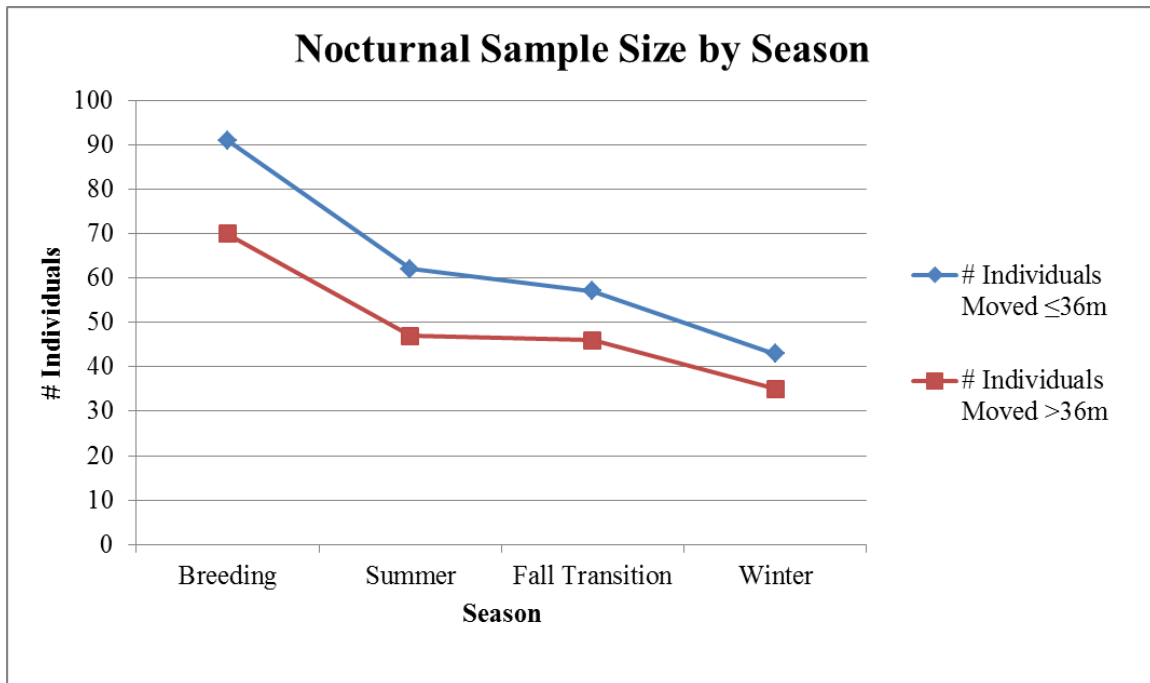


Figure 4.2. Number of lesser prairie-chickens (*Tympanuchus pallidicinctus*) contributing to nocturnal roost site selection samples by season from April 2013-May 2016 in Beaver County, OK. Colors indicate if individual moved more or less than 36 m, which was double our average GPS error.

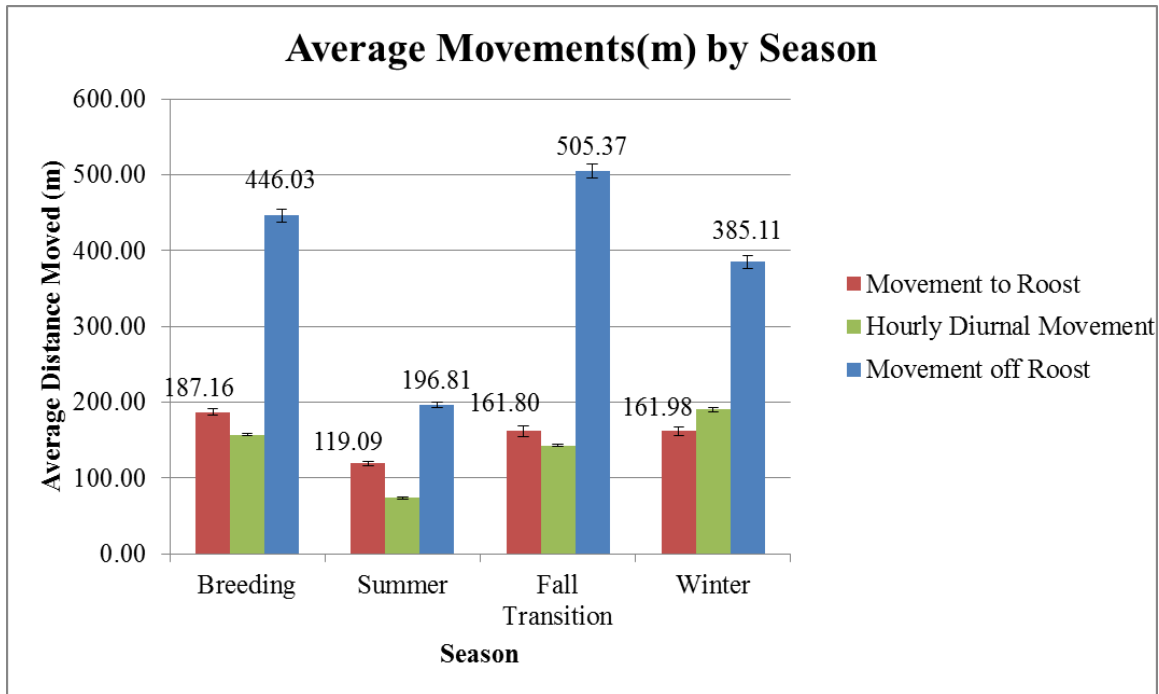


Figure 4.3. Average movement of lesser prairie-chickens (*Tympanuchus pallidicinctus*) to and from roost sites as well as their average diurnal movements by season in Beaver County, OK from April 2013-May 2016. Numbers represent maximum average distances observed and standard error bars are presented.

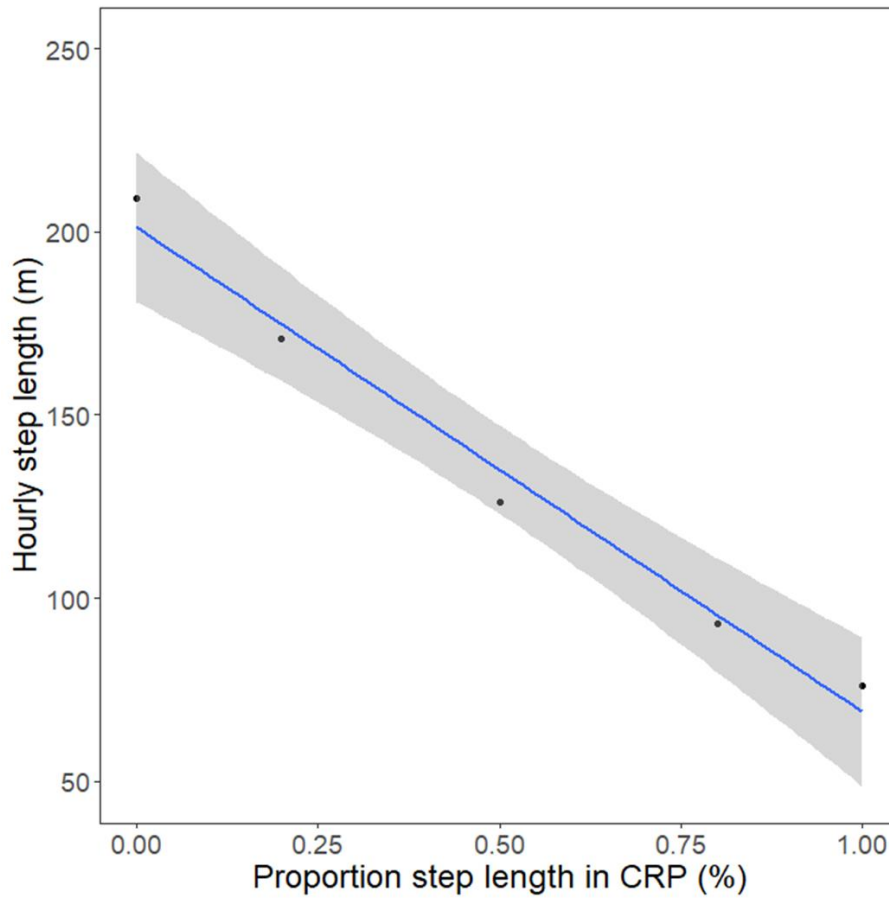


Figure 4.4. Relationship between the proportion of a lesser prairie chicken's (*Tympanuchus pallidicinctus*) movement to a roost site contained within CRP and the mean hourly step length of the movement to a roost site as determined from a GLMM. Data are from individuals in Beaver County, OK from April 2013-May 2016.

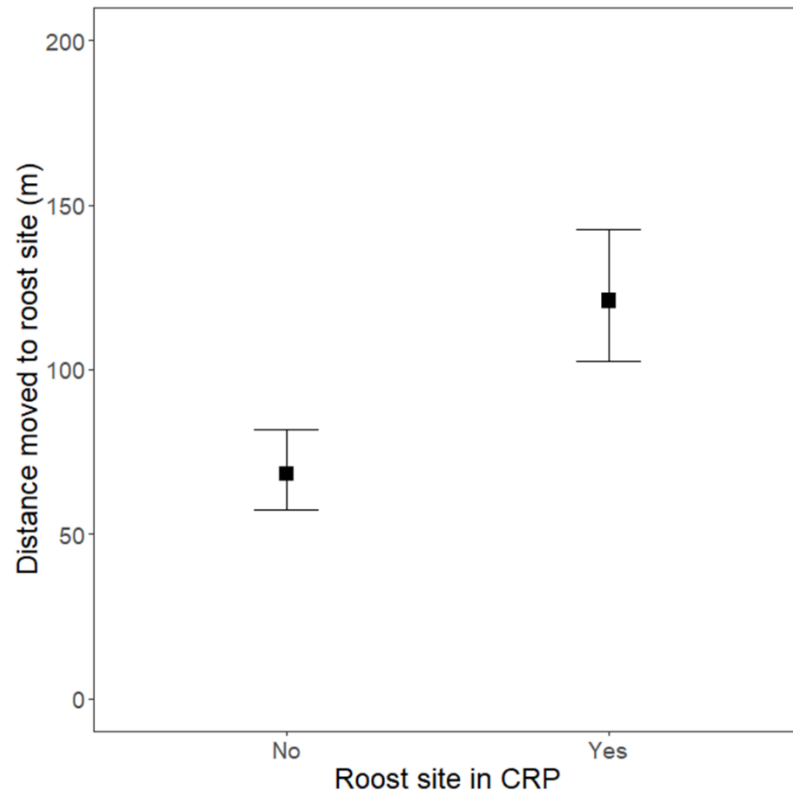


Figure 4.5. Relationship between whether or not a roost site of a lesser prairie chicken (*Tympanuchus pallidicinctus*) was located in CRP and the mean hourly step length of the movement to a roost site as determined from a GLMM. Data are from individuals in Beaver County, OK from April 2013-May 2016.

DISCUSSION AND SUMMARY

Our research provides a multi-spatial-scale assessment of the importance of CRP enrollment on the LPC distribution, third-order (Johnson 1980) habitat use, and movement patterns through a collation of disparate data sets. Barring our species distribution model built entirely with occurrences having a roadside bias (i.e., the eBird data sets), all other models indicated a positive relationship with the presence of CRP and spatial patterns for the LPC across all examined scales, indicating this relationship was scale-invariant (Gisiger 2001) and that CRP was a primary driver of space use (Northrup et al. 2016). Our results, along with a growing body of literature, suggest that patches of CRP are playing a key role in maintaining useable space throughout the LPC distribution by maintaining grassland connectivity (Tanner and Fuhlendorf 2018) for a species that requires large spatial extents of habitat. Furthermore, by incorporating temporal variability associated with drought conditions into our distribution models, we illustrate that patches of CRP maintain their importance as environmental conditions and vegetation cover varies. Within the LPC distribution, the CRP primarily functions to establish permanent grassland vegetation on former croplands (Stubbs 2014), and population resilience of the LPC has been shown to decrease as grassland cover decreases and landscapes exceed 9.6% cropland during drought conditions (Ross et al. 2016). By incorporating spatially explicit CRP data into our temporal species distribution models, our results corroborate the important contributions that the CRP plays in influencing environmental suitability during drought conditions, which are expected to increase within the Central Plains in future decades (Cook et al. 2015).

Conversely, when assessing the impact of anthropogenic features to spatial patterns of LPCs across spatial scales, we detected scale-specific variation in the importance of these features. At a broad grain (~5 km) across the species' distribution, we found that, variables associated with anthropogenic features (i.e., oil/gas well density and human footprint) consistently exhibited a negative relationship with the probability of LPC environmental suitability (Figures 1.4-1.6). Though these variables contributed <16% to model accuracy gain, the consistency of the relationships corroborate the findings of other local studies within the LPC distribution that have reported negative effects of oil and gas developments (Pitman et al. 2006, Beck 2009, Timmer et al. 2014, Sullins et al. 2019). However, at finer spatial scales (30 m grain and county-level spatial extent), we found that CRP and the cover of functional plant groups contributed more to environmental suitability than did the distance from anthropogenic features (Table 2.3). Avoidance of anthropogenic features may not be an absolute pattern for the LPC and can vary by region based on feature densities (Sullins et al. 2019) and/or by life-history stages of individuals (Lautenbach et al. 2017). Furthermore, access to habitat provided by CRP may outweigh the negative influences of anthropogenic features at lower densities (Plumb et al. 2019), a pattern that was evident in our smaller-scale distribution models and through our roost site selection analysis.

Assessing species distribution models with disparate data sets could highlight the inherent complexities of species' specific relationships with environmental variables across space. For instance, the relationship between CRP and the probability of LPC environmental suitability was opposite across the aerial survey/joint models when compared to the eBird model (Figures 1.4-1.6). Such a paradox could be related to the fact that the effects of CRP on the probability of LPC environmental suitability are not uniform across their distribution, which may be attributed to variation in regional availability of CRP, or to regional variation in the quality of CRP (i.e., planted in natives versus non-native species). Land enrolled in the CRP has been identified as critical to LPC habitat throughout portions of their distribution (Jarnevich and Laubhan 2011; Spencer et al. 2017; Sullins et al. 2018). Yet, this relationship likely varies based on the spatial scale and the landscape matrix that surrounds CRP land cover (Fuhlendorf et al. 2002; Sullins et al. 2018). Furthermore, such a discrepancy in the relationship between CRP and LPC suitability may arise due to differences in detection probabilities and sampling effort across occurrence datasets (Higa et al. 2015) in which roadside observations in the eBird dataset may have decreased detection probabilities due to visual obstruction associated with CRP vegetation. Considerations regarding detection probabilities across datasets should be considered when making interpretations.

Cover of CRP can play an important role in providing usable space for a plethora of species (Luttschwager and Higgins 1992, Herkert 1998, Hagen et al. 2016) yet these relationships are likely to vary based on the Conservation Practice of each CRP patch, the surrounding matrix in which the CRP is located, and the configuration of CRP relative to the rest of the landscape (Batáry et al. 2011). The results from county-level species distribution models suggested that CRP was influential in determining environmental suitability for the LPC, but not for northern bobwhite or scaled quail. Though bobwhite have been shown to use CRP patches in other parts of its distribution (Osborne et al. 2012), it is likely that we did not detect a similar pattern as this species was primarily restricted to shrublands, such as sand sagebrush (*Artemisia filifolia*) vegetation communities associated with the Beaver River, which has a terrain not conducive to establishing croplands and thus was less likely to have CRP enrollment from past land use practices. Similarly, environmental suitability for scaled quail was not influenced by CRP patches relative to other environmental variables, a pattern that has been suggested before (Schemnitz 1993). Despite this, we did estimate areas of range overlap which fluctuated with drought conditions, with greater amounts of range overlap occurring for both northern bobwhite/LPC and scaled quail/LPC during 2013 (8.5% and 33.5%, respectively [Figures 2.2 and 2.3]) when compared to 2015 (4% and 5%, respectively [Figures 2.2 and 2.3]). This may suggest behavioral plasticity between these three Galliformes relative to their potential range overlap and the environmental conditions and the associated vegetation cover on the landscape.

Beyond the influence of Conservation Practices and spatial organization of CRP patches on potential wildlife benefits, discrete disturbance events (associated with mid-contract management) may also influence how LPCs benefit from CRP patches. Indeed, the

implementation of mid-contract management practices has been shown to provide benefits for many species using CRP patches (Negus et al. 2010, Osborne et al. 2012). Grazing has been an ecological process that LPCs evolved with (Copelin 1963), though changes in grazing systems and stocking rates can negatively influence usable space for individuals (Bailey et al. 2000, Hagen et al. 2004). Through an assessment of movement patterns (a fundamental characteristic of organisms that are influenced by multiple processes across scales [Nathan et al. 2008]) of LPC associated with a lek within a CRP patch experiencing managed grazing during mid-contract management, we saw no direct evidence of this mid-contract management on movement patterns. Similarly, we found little change in vegetation conditions during this managed grazing, with only vegetation height being significantly different post-grazing. Though movement patterns were greater after managed grazing, this same pattern was seen with our control population not associated with this grazing event (Figure 3.1). Moreover, though we estimated a higher probability of moving during the managed grazing period (Figure 3.2), this same pattern was observed in our control population. When assessing how much of a movement was included in the CRP patch experiencing mid-contract grazing, we estimated statistically similar step lengths when 100% of the movement was in the CRP patch being grazed (Figure 3.4), and individuals had lower movement when the movement both started and ended in the grazed CRP patch, similar to our control population (Figure 3.5). Our study provides evidence that managed grazing that is regulated by the NRCS did not significantly alter movement patterns of LPC using the grazed CRP relative to the rest of the population, and that actual differences in movement patterns across our “grazing periods” was likely a reflection of seasonal changes (Figure 4.1).

Finally, our research provides the first assessment of how CRP influences nocturnal roost site selection for LPCs, an understudied aspect of their life-history (Lima et al. 2005). Based on global models, vegetation was more important in determining roost site selection than compared to anthropogenic features (Table 4.2). Of all vegetation categories included in our analysis, CRP was the most influential, in which LPCs selected roost sites closer to CRP patches than would be expected at random. Furthermore, CRP influenced that movements of LPCs to roost site locations based on their last recorded location before sunset. Specifically, LPCs move further to select roost sites in CRP if their previous location was not located in CRP, yet movements to roost sites in CRP significantly decrease if the individual was already located in CRP before sunset. Conversely, individuals avoided vegetation types associated with low vegetation and shrubs (Table 4.3), indicating that roost site selection is driven by vegetation structure characteristic of mixed grass prairies and CRP. This is consistent with the limited information previously published on roost site selection (Davis et al. 1979, Riley et al. 1993), however our research is the first to illustrate how CRP changes movement patterns to nocturnal roost sites. Considering that all animals must select sites to rest and may spend a large portion of their lives doing so (Lima et al. 2005), understanding what influences the movements of LPC to these important sites during a vulnerable period in an organism’s life is critical to conservation, particularly when considering energetics associated with longer versus shorter movements (Halsey 2016). By implementing CRP

enrollment onto a landscape, an increase for both diurnal and nocturnal usable space may result for LPCs.

CONSERVATION RECOMMENDATIONS AND FUTURE RESEARCH OPPORTUNITIES

Below we have outlined conservation recommendations and the future research needs relating to the implementation of CRP and how it influences LPC ecology across multiple scales. This is not an exhaustive list and we attempt to provide recommendations without over-extrapolating the results provided in this report.

- Broadly, we provide evidence on the functionality of CRP enrollment as a way to maintain large areas of grasslands and promote grassland connectivity that directly influences the habitat suitability for the LPC. Efforts to maintain and promote CRP enrollment in areas where grasslands are lacking should be promoted.
- Though CRP has a direct influence on habitat suitability of the LPC, it is clear that heterogeneity of land cover types will likely benefit the LPC more than a homogenous landscape of CRP. This was evident based on niche models created using aerial survey data and a combination of aerial survey and eBird data, in which the probability of suitability for LPCs within a 25km² matrix increased by <25% when this area increased from 0% CRP to 100% CRP. Thus, there is likely a threshold in which there are potentially diminishing returns on more CRP coverage within the LPC distribution, and this warrants further research to explore where a threshold may exist.
- With further regard to our species distribution models, we highlight the potential that open source citizen science data has for providing supplemental data for distribution models of the LPC. However, we note that these data must be vetted carefully if they are to be included in conservation decisions through pre-modelling filtering protocols and assessment of spatial and temporal biases. Nonetheless, these data can be collated with existing standardized data to provide a low-cost supplement that provides spatially unique data for distribution models.
- The use of northern bobwhite and scaled quail management as an umbrella approach to help benefit LPC conservation is likely not warranted. Disparity in space use estimated through ecological niche models suggests that areas that benefit LPCs are more often spatially unique when compared to northern bobwhite and scaled quail.
- Though our research related to mid-contract management was restricted to a single lekking site and represents only one type of management practice (managed grazing), our results suggest that the mid-contract management associated with individuals in our study did not influence LPC movement patterns during this practice. This potentially highlights that managers and conservation scientists should think about habitat quantity rather than quality or composition in human influenced matrices within the LPC distribution. However, our sample size

- is limited and future research should explore how the timing and specific mid-contract management practice may change these relationships.
- CRP plays an important role in influencing the distance a LPC will travel to select a roost site. Furthermore, we show that individuals will rarely travel >0.5 km to or from a roost site throughout the year. Given these parameters, considerations should be made in the spatial arrangement and nearest neighbors of CRP patches if they are to provide maximum benefits for roost sites. Future research should examine demographic parameters (i.e., survival) associated with roost site selection both within and outside of CRP patches to better understand if one patch type functions as a potential sink.
 - A better understanding of the optimal spatial arrangement of CRP for LPCs is needed in future research endeavors. We propose addressing this need through the integrated use of movement ecology theory (through GPS locations) and agent-based modeling, which will help highlight the optimum arrangement and patch size of CRP for the benefit of LPC populations.

LITERATURE CITED

- Archer, S. 1994. Woody plant encroachment into southwestern grassland and savannas: rates, patterns and proximate causes. In: Vavra, M. W. A. Laycock, and R. D. Pieper (eds) Ecological implications of livestock herbivory in the West. Society for Range Management, Denver, Colorado, USA, pp. 13-68.
- Bailey, J. A., J. Klingel, and C. A. Davis. 2000. Status of nesting habitat for Lesser prairie-chicken in New Mexico. *Prairie Naturalist* 32:49-156.
- Batáry, P., A. Báldi, D. Kleijn, and T. Tschardt. 2011. Landscape-moderated biodiversity effects of agri-environmental management: a meta-analysis. *Proceedings of the Royal Society B* 278:1894-1902.
- Beck, J. L. 2009. Impacts of oil and natural gas on prairie grouse: current knowledge and research needs. *Proceedings of the 2009 National Meeting – American Society of Mining and Reclamation* 26:66-87.
- Bedrosian, B., and D. Craighead. 2007. Evaluation of techniques for attaching transmitters to common raven nestlings. *Northwestern Naturalist* 88:1-6.
- Ben-Akiva, M., and S. R. Lerman. 1985. Discrete choice analysis: theory and application to travel demand. MIT press, Cambridge, Massachusetts, USA.
- Boyce, M. S., P. R. Vernier, S. E. Nielsen, and F. K. A. Schmiegelow. 2002. Evaluating resource selection functions. *Ecological Modeling* 157:281-300.
- Brennan, L. A., and W. P. Kuvlesky, Jr. 2005. North American grassland birds: an unfolding conservation crisis? *Journal of Wildlife Management* 69:1-13.

- Brown, J. L., 2014. SDMtoolbox: a python-based GIS toolkit for landscape genetic, biogeographic, and species distribution model analyses. *Methods in Ecology and Evolution* 5:694-700.
- Burnham, K. P., and D. R. Anderson. 2002. Model selection and inference: a practical information-theoretic approach. Springer-Verlag, New York, New York, USA.
- Collins, S. L., J. A. Bradford, and P. L. Sims. 1987. Succession and fluctuation in *Artemisia* dominated grassland. *Vegetatio* 83:89-99.
- Columbia University. 2005. Wildlife Conservation Society and Center for International Earth Science Information Network. Last of the Wild Project, Version 2, 2005 (LWP-2): Global Human Footprint Dataset (Geographic). Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). <http://dx.doi.org/10.7927/H4M61H5F>.
- Copelin, F. F. 1963. The lesser prairie-chicken in Oklahoma. Oklahoma Department of Wildlife Technical Bulletin 6, Oklahoma City, Oklahoma, USA.
- Cook, B. I., T. R. Ault, and J. E. Smerdon. 2015. Unprecedented 21st century drought risk in the American Southwest and Central Plains. *Science Advances* 1:e140082.
- Cooper, A. B., and J. J. Millspaugh. 1999. The application of discrete choice models to wildlife resource selection studies. *Ecology* 80:566-575.
- Daubenmire, R. F. 1959. A canopy-cover method of vegetation analysis. *Northwest Science* 33:43-46.
- Davis, C. A., T. Z. Riley, J. R. Suminski, and M. J. Wisdom. 1979. Habitat evaluation of lesser prairie chickens in eastern Chaves County, New Mexico. Final Report to Bureau of Land Management, Roswell. Department of Fishery and Wildlife Science, New Mexico State University, Las Cruces, USA.
- Delisle, J. M., and J. A. Savidge. 1997. Avian use and vegetation characteristics of Conservation Reserve Program fields. *Journal of Wildlife Management* 61:318-325.
- Diamond, D. D., and L. F. Elliott. 2015. Oklahoma Ecological Systems Mapping Interpretive Booklet: Methods, Short Type Descriptions, and Summary Results. Oklahoma Department of Wildlife Conservation, Norman, Oklahoma, USA.
- Donald, P. F., and A. D. Evans. 2006. Habitat connectivity and matrix restoration: the wider implications of agri-environmental schemes. *Journal of Applied Ecology* 43:209-218.
- Drummond, M. A., R. F. Auch, K. A. Karstensen, K. L. Sayler, J. L. Taylor, and T. R. Loveland. 2012. Land change variability and human-environment dynamics in the United States Great Plains. *Land Use Policy* 29:710-723.
- Elith, J. 2002. Quantitative methods for modeling species habitat: comparative performance and an application to Australian plants. In: Ferson, S., and M. Burgman (ed), *Quantitative Methods for Conservation Biology*. Springer-Verlag, New York, pp. 39-58.

- Elith, J., S. J. Phillips, T. Hastie, M. Dudik, Y. E. Chee, and C. J. Yates. 2011. A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions* 17:43-57.
- Engle, D. M., T. G. Bidwell, and M. E. Mosely. 1995. Invasion of Oklahoma rangelands and forests by eastern redcedar and ashe juniper. Oklahoma State University, Oklahoma Cooperative Extension Service Circular E-947. Stillwater, Oklahoma, USA.
- ESRI 2011. ArcGIS Desktop: Release 10. Environmental Systems Research Institute, Redlands, California, USA.
- Fielding, A. H., and J. F. Bell. 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation* 24:38-49.
- Fuhlendorf, S. D., and D. M. Engle. 2001. Restoring heterogeneity on rangelands: ecosystem management based on evolutionary grazing patterns. *BioScience* 51:625-632.
- Fuhlendorf, S. D., A. J. W. Woodward, D. M. Leslie, and J. S. Shackford. 2002. Multi-scale effects of habitat loss and fragmentation on lesser prairie-chicken populations of the US Southern Great Plains. *Landscape Ecology* 17:617-628.
- Gisiger, T. 2001. Scale invariance in biology: coincidence or footprint of a universal mechanism? *Biological Reviews* 76:161-209.
- Hagen, C. A. 2010. Impacts of energy development on prairie grouse ecology: a research synthesis. Transactions for the 75th North American Wildlife and Natural Resources Conference 75:96-103.
- Hagen, C. A., B. E. Jamison, K. M. Giesen, and T. Z. Riley. 2004. Guidelines for managing lesser prairie-chicken populations and their habitats. *Wildlife Society Bulletin* 32:69-82.
- Hagen, C. A., D. C. Pavlacky, Jr., K. Adachi, F. E. Hornsby, T. J. Rintz, and L. L. McDonald. 2016. Multiscale occupancy modeling provides insights into range-wide conservation needs of Lesser Prairie-Chickens (*Tympanuchus pallidicinctus*) *Condor* 118: 597-612.
- Halsey, L. G. 2016. Terrestrial movement energetics: current knowledge and its application to the optimising animal. *Journal of Experimental Biology* 219:1424-1431.
- Haukos, D. A., L. M. Smith, and G. S. Broda. 1990. Spring trapping of lesser prairie-chickens. *Journal of Field Ornithology* 61:20-25.
- Herkert, J. R. 1998. The influence of the CRP on grasshopper sparrow population trends in the mid-continental United States. *Wildlife Society Bulletin* 26:227-231.
- Higa, M., Y. Yamaura, I. Koizumi, Y. Yabuhara, M. Senzaki, and S. ono. 2015. Mapping large-scale bird distributions using occupancy models and citizen data with spatially biased sampling effort. *Diversity and Distributions* 21:46-54.
- Hirzel, A. H., G. Le Lay, V. Helfer, C. Randin, and A. Guisan. 2006. Evaluating the ability of habitat suitability models to predict species presences. *Ecological Modeling* 199:142-152.

- Hovick, T. J., R. D. Elmore, D. K. Dahlgren, S. D. Fuhlendorf, and D. M. Engle. 2014. Evidence of negative effects of anthropogenic structures on wildlife: A review of grouse survival and behavior. *Journal of Applied Ecology* 51:1680-1689.
- Hunt, J. L., and T. Best. 2010. Vegetative characteristics of active and abandoned leks of lesser prairie-chicken (*Tympanuchus pallidicinctus*) in southeastern New Mexico. *Southwestern Naturalist* 55:477-487.
- Jarnevich, C. S., and M. K. Laubhan. 2011. Balancing energy development and conservation: a method utilizing species distribution models. *Environmental Management* 47:926-936.
- Johnson, D. H. 1980. The comparison of usage and availability measurements for evaluating resource preference. *Ecology* 61:65-71.
- Jones, M. O., B. W. Allred, D. E. Naugle, J. D. Maestas, P. Donnelly, L. J. Metz, J. Karl, R. Smith, B. Bestelmeyer, C. Boyd, J. D. Kerby, and J. D. McIver. 2018. Innovation in rangeland monitoring: annual, 30 m, plant functional type percent cover maps for U.S. rangelands, 1984-2017. *Ecosphere* 9:e02430.
- Knopf, F. L. 1994. Avian assemblages on altered grasslands. *Studies in Avian Biology* 15:247-257.
- Kukal, C. A. 2010. The over-winter ecology of lesser prairie-chickens (*Tympanuchus pallidicinctus*) in the northeast Texas Panhandle. These. Texas Tech University.
- LANDFIRE. 2013. Existing Vegetation Type layer. U.S. Department of Interior, Geological Survey. <http://landfire.cr.usgs.gov>.
- Lautenbach, J. M., R. T. Plumb, S. G. Robinson, C. A. Hagen, D. A. Haukos, and J. C. Pitman. 2017. Lesser prairie-chicken avoidance of trees in a grassland landscape. *Rangeland Ecology and Management* 70:78-86.
- Lima, S. L., N. C. Rattenborg, J. A. Lesku, and C. J. Amlaner. 2005. Sleeping under the risk of predation. *Animal Behavior* 70:723-736.
- Luttschwager, K. A., and K. F. Higgins. 1992. Nongame bird, game bird, and deer use of Conservation Reserve Program fields in eastern South Dakota. *Proceedings of the South Dakota Academy of Sciences* 71:31-36.
- Meyer, W. B. 1995. Past and present land use and land cover in the USA. *Consequences* Spring, pp. 25-33.
- McCracken, M. L., B. F. J. Manly, and M. Vander Heyden. 1998. Use of discrete-choice models for evaluating resource selection. *Journal of Agricultural, Biological, and Environmental Statistics* 3:268-279.
- Nathan, R., W. M. Getz, E. Revilla, M. Holyoak, R. Kadmon, D. Saltz, and P. E. Smouse. 2008. A movement ecology paradigm for unifying organismal movement research. *PNAS* 105:19052-19059.

- Negus, L. P., C. A. Davis, and S. E. Wessel. 2010. Avian response to mid-contract management of Conservation Reserve Program Fields. *American Midland Naturalist* 164:296-310.
- Northrup, J. M., C. R. Anderson, M. B. Hooten, and G. Wittemyer. 2016. Movement reveals scale dependence in habitat selection of a large ungulate. *Ecological Applications* 26:2746-2757.
- Oksanen, J. R. Kindt, P. Legendre, B. O'Hara, G. I. Simpson, P. Solymos, M. H. H. Stevens, and H. Wagner. 2015. *Vegan: Community Ecology Package*. R. package Version 2.5-6.
- Osborne, D. C., D. W. Sparling, and R. L. Hopkins II. 2012. Influence of conservation reserve program mid-contract management and landscape composition on northern bobwhite in tall fescue monocultures. *Journal of Wildlife Management* 76:566-574.
- Phillips, S. J., R. P. Anderson, and R. E. Schapire. 2006. Maximum entropy modeling of species geographic distributions. *Ecological Modeling* 190:231-259.
- Pitman, J. C., C. A. Hagen, B. E. Jamison, R. J. Robel, T. M. Loughin, and R. D. Applegate. 2006. Nesting ecology of lesser prairie-chickens in sand sagebrush prairie of southwestern Kansas. *Wilson Journal of Ornithology* 118:23-35.
- Plumb, R. T., J. M. Lautenbach, S. G. Robinson, D. A. Haukos, V. L. Winder, C. A. Hagen, D. S. Sullins, J. C. Pitman, and D. K. Dahlgren. 2019. Lesser prairie-chicken space use in relation to anthropogenic structures. *Journal of Wildlife management* 83:216-230.
- Ratajczak, Z., J. B. Nippert, and S. L. Collins. 2012. Woody encroachment decreases diversity across North American grasslands and savannas. *Ecology* 93:697-703.
- Riley, T. Z., C. A. Davis, and R. A. Smith. 1993. Autumn-winter habitat use of the lesser prairie-chicken (*Tympanuchus pallidicinctus*) (*Galliformes: ternaonidae*). *Great Basin Naturalist* 53:409-411.
- Robel, R. J., J. N. Briggs, A. D. Dayton, and L. C. Hulbert. 1970. Relationships between visual obstruction measurements and weight of grassland vegetation. *Journal of Range Management* 23:295-297.
- Ross, B. E., D. A. Haukos, C. A. Hagen, and J. C. Pitman. 2016. Landscape composition creates a threshold influencing lesser prairie-chicken population resilience to extreme drought. *Global Ecology and Conservation* 6:179-188.
- Samson, F., and F. Knopf. 1994. Prairie conservation in North America. *BioScience* 44:418-421.
- Schemnitz, S. D. 1993. Scaled quail habitats revisited – Oklahoma Panhandle. *National Quail Symposium Proceedings* 3:20.
- Silvy, N. J. 2006. In my opinion: shinnery oak is not a requirement for lesser prairie-chicken habitat. Pages 138-142 in *Proceedings of the Symposium on Managing Wildlife in the Southwest: New Challenges for the 21st Century*. J. W. Cain III and P. R. Krausman, editors.

- Spencer, D., D. A. Haukos, C. A. Hagen, M. Daniels, and D. Goodin. 2017. Conservation reserve program mitigates grassland loss in the lesser prairie-chicken range of Kansas. *Global Ecology and Conservation* 9:21-38.
- Stoddard, H. L. 1931. The bobwhite quail: its habits, preservation, and increase. Charles Scribner's Sons, New York, New York, USA.
- Stubbs, M. 2014. Conservation provisions in the 2014 Farm Bill (P.L. 113-79). CRS Reports R43504.
- Sullins, D. S., J. D. Kraft, D. A. Haukos, S. G. Robinson, J. H. Reitz, R. T. Plumb, J. M. Lautenbach, J. D. Lautenbach, B. K. Sandercock, and C. A. Hagen. 2018. Demographic consequences of conservation reserve program grasslands for lesser prairie-chickens. *Journal of Wildlife Management* 82:1617-1632.
- Sullins, D. S., D. A. Haukos, J. M. Lautenbach, J. D. Lautenbach, S. G. Robinson, M. B. Rice, B. K. Sandercock, J. D. Kraft, R. T. Plumb, J. H. Reitz, J. M. Shawn Hutchinson, and C. A. Hagen. 2019. Strategic conservation for lesser prairie-chickens among landscapes of varying anthropogenic influence. *Biological Conservation* 238:108213.
- Swets, J. A. 1988. Measureing the accuracy of diagnostic systems. *Science* 240:1285-1293.
- Tanner, E. P., and S. D. Fuhlendorf. 2018. Impact of an agri-environmental scheme on landscape patterns. *Ecological Indicators* 85:956-965.
- Taranu, Z. E., I. Gregory-Eaves, R. J. Steele, M. Beaulieu, and P. Legendre. 2017. Predicting microcystin concentrations in lakes and reservoirs at a continental scale: A new framework for modelling and important health risk factor. *Global Ecology and Biogeography* 26:625-637.
- Timmer, J. M., M. J. Butler, W. B. Ballard, C. W. Boal, and H. A. Whitlaw. 2014. Spatially explicit modeling of lesser prairie-chicken lek density in Texas. *Journal of Wildlife Management* 78:142-152.
- Unger, A. M. 2017. Playing chicken: at the intersection of anthropogenic development and lesser prairie-chickens. Dissertation. Oklahoma State University, Stillwater, Oklahoma.
- Warren, D. L., R. E. Glor, and M. Turelli. 2008. Environmental niche equivalency versus conservatism: quantitative approaches to niche evolution. *Evolution* 62:2868-2883.
- Warren, D. L., R. E. Glor, and M. Turelli. 2010. ENMTools (Version 1.4.4): A toolbox for comparative studies of environmental niche models. *Ecography* 33:607-611.
- Wilson, J. W., J. O. Sexton, R. T. Job, and N. M. Haddad. 2013. The relative contribution of terrain, land cover, and vegetation structure indices to species distribution models. *Biological Conservation* 164:170-176.

- Wolfe, D. H., M. A. Patten, E. Schochat, C. L. Pruett, and S. K. Sherrod. 2007. Causes and patterns of mortality in lesser prairie-chickens (*Tympanuchus pallidicinctus*) and implications for management. *Wildlife Biology* 13:95-104.
- Zuur, A. F., and E. N. Ieno. 2016. *Beginners guide to zero-inflated models with R*. Newburgh, U.K.: Highland Statistics Ltd.